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ASSESSING PREDICTORS OF SMOKING CESSATION:
AN APPLICATION OF SIGNAL DETECTION METHODOLOGY

BY

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A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE
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ABSTRACT

Cigarette smoking is a leading cause of preventable illness and death in the United States. Yet, when people are able to quit, the negative effects of smoking to their health diminish over time. For this reason, it is important for behavioral scientists to understand the mechanisms which underly smoking cessation. In this study, signal detection analysis was used to determine which baseline characteristics of 602 smokers were best able to discriminate those who had quit smoking from those who had not six and eighteen months later. Variables included in this analysis were chosen based on prior research showing that they were correlated with smoking cessation. These included variables from the Transtheoretical model, and also addiction and perceived stress.

Three algorithms were developed using signal detection methodology which identified subgroups of individuals who were highly likely and unlikely to quit smoking. The variables which were consistently able to discriminate outcome for certain subgroups were perceived stress, and variables from the Transtheoretical model such as self-efficacy, the benefits of smoking, and the experiential processes of change. These findings have implications as to which subgroups have particular low rates of smoking cessation and what types of interventions may be most effective to help these individuals quit. A step-care approach to interventions using the Transtheoretical model based on subgroup characteristics is suggested.

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Introduction

Cigarette smoking is the leading cause of preventable illness and death in the United States. The Public Health Service reports that cigarette smoking accounts for about 400,000 deaths a year in the U.S. and that approximately half of all cigarette smokers will eventually die from smoking related causes (USDHHS, 1995). There are well established links between smoking and heart disease, cancer, chronic obstructive pulmonary disease, bronchitis, and emphysema (CDC, 1993; Fielding, 1985). Average reduction in life expectancy of those who smoke twenty to forty cigarettes a day is five to eight years (Fielding, 1985).

There is also strong evidence to support that second hand smoke, the inhalation of smoke from other peoples' cigarettes, can have negative health consequences. A meta-analysis conducted by Wu (1990) revealed an elevated risk of lung cancer in people exposed to second hand smoke. Children of smokers have been shown to have a greater incidence of respiratory illness (Stoddard & Miller, 1995; USDHHS, 1984a).

Yet, approximately 23% of adults in the United States are current smokers (Massachusetts Medical Society, 1997). If these people were to quit, the negative effects to their health of their years of smoking would diminish over time, until their risk level of many diseases would be no greater than those of non-smokers. For example, a 1990 surgeon general's report (USDHHS, 1990) stated that former light smokers (those who had smoked less than twenty cigarettes a day) had the same mortality rates as those who had never smoked after sixteen years of abstinence. In male heavy smokers, the death

risk is 2.73 times greater than for those who have never smoked. However, after sixteen years of abstinence, their mortality rate is reduced by about a half and is only slightly higher than for those who have never smoked. These statistics show the benefits of quitting smoking and the importance of behavioral scientists to help people make this behavior change.

The Transtheoretical Model

One model which has been applied to the area of behavior change is the Transtheoretical model. This model is extensive and integrative in that it encompasses many of the strongest variables of other behavior change theories, such as the self-efficacy construct from Social Cognitive theory (Bandura, 1977, 1986) and Janis and Mann's (1977) theory of decisional balance. The basis of the Transtheoretical model is that there are common processes and principles that underlie how people change their behavior. These processes and principles are integrated in the model through the stages of change, a series of five stages that are differentiated based on a temporal domain. The principles behind the Transtheoretical model have been found to hold whether people change on their own or with the help of an intervention (Prochaska & Velicer, 1997). The Transtheoretical model has been applied successfully to a wide range of health behaviors, including exercise (Marcus, Selby, Niaura, and Rossi, 1992), excessive alcohol consumption (DiClemente & Hughes, 1990), sun exposure (Rossi, Blais, Redding, & Weinstock, 1995), and dietary fat intake (Greene, Rossi, Reed, Willey, & Prochaska, 1994). Application of the model to these health behaviors has shown that the use of certain constructs can help predict successful behavior change. These constructs include

decisional balance between the pros and cons of behavior change, processes of change, and self-efficacy. By identifying these predictors and communicating to people how to use them most effectively, the Transtheoretical model can be used to design interventions to help people progress through the stages of change for smoking cessation. Also, by integrating aspects of other models, the Transtheoretical model gives a framework for researchers to examine how these various constructs work in combination with each other to predict smoking cessation outcome. An explanation and literature review of the constructs included in the Transtheoretical Model, covering stages of change, decisional balance, self-efficacy, and process of change are presented in Appendix A.

Other Variables

Variables outside of the Transtheoretical model that have also been found to be successful predictors of smoking cessation include perceived stress (Cohen, Kamarch, & Mermelstein, 1983; Cohen & Williamson, 1987) and level of physical dependence on nicotine (Fagerstrom, 1978).

Perceived Stress. Although stressful events occur in the lives of all individuals, it is the cognitive appraisal of these events that determines the effect of the stressor on an individual's health (e.g. Lazarus, 1977). Correlations have been found between perceived stress and average number of cigarettes smoked per day. Also, changes in perceived stress have been correlated with changes in average number of cigarettes smoked per day (Cohen, Kamarck, and Mermelstein, 1983).

Addiction to Smoking. Addiction to smoking has been found to correlate with heart rate increases during smoking and changes in body temperature following smoking cessation (Fagerstrom, 1978). Addiction has also been shown to predict smoking cessation outcome, with those who have a higher level of addiction being less likely to quit and not relapse (Pinto, Abrams, Monti, & Jacobus, 1987). However, researchers have found that it is difficult to separate the physical aspects from the psychological aspects of addiction to cigarette smoking (Fagerstrom, 1978; Payne, Smith, McCracken, McSherry, Antony, 1994). This can make it difficult to ascertain whether addiction variables really account for differences in abilities to quit smoking, or whether there is something else going on. For example, Rossi, Prochaska, and DiClemente (1988) found that light smokers used more behavioral processes than heavy smokers to help them quit. This is an alternative explanation to Pinto and colleagues' findings.

Signal Detection Methodology

Signal detection methodology (SDM) has the potential to make several unique contributions to our knowledge in the area of smoking cessation. First, signal detection can help to identify subgroups of smokers who are most and least likely to succeed at quitting. Signal detection is also useful in the development of an algorithm for assigning people to the most appropriate treatment. Because this algorithm is in the form of a simple tree diagram, rather than made up of weighted sums, it can easily be used in clinical settings. Finally, signal detection can help behavioral scientists to understand

which variables are the strongest discriminators of those who are able to quit smoking from those who are not.

In SDM, independent variables are seen as tests which are evaluated for their ability to classify people correctly. The dependent variable is the dichotomous outcome where people are classified to one of two categories. In the present study, the tests which were analyzed were baseline variables described above, and outcome was point-prevalence smoking status six and eighteen months after baseline.

Subgroup Identification. One way in which signal detection can contribute to our current understanding of the smoking cessation process is by identifying subgroups of people who show different patterns of behavior for whom specifically tailored interventions may be necessary. Much literature has expressed the need for identifying subgroups of individuals who may have special needs or interests (e.g. Fagerstrom, 1978; Grunig, 1989; Norman, Velicer, Fava, & Prochaska, 1998; Williams & Flora, 1997). Theory from the field of communication calls for segmentation (Grunig, 1989), a campaign planning strategy that addresses homogeneous subgroups based on certain defining characteristics. In the area of public health, segmentation is used to design health messages that are appealing to subgroups with specific attitudes, behaviors, preferences, and patterns of media use (Williams & Flora, 1997). Clinical interventions should also be designed with meaningful subgroups in mind (King, Kiernan, Oman, Kraemer, Hull, & Ahn, 1997). Signal detection classifies participants into distinct subgroups which are mutually exclusive and maximally differentiated from each other based on the outcome variable (King, et al., 1997; Williams & Flora, 1997).

Algorithm Development. Signal detection is useful in developing algorithms in the form of 'and/or' decision rules that are relatively easy to apply in clinical settings. Other methods such as discriminant function analysis and logistic regression result in scores based on weighted sums which are more difficult to interpret and less likely to be used in a clinical setting (Killen, Fortmann, Kraemer, Varady, & Newman, 1992). One example of the potential clinical usefulness of SDM is that the cut-off points determined through the algorithm can be used in interventions such as computer based Expert Systems (Velicer, Prochaska, Bellis, DiClemente, Rossi, Fava, & Steiger, 1993).

Actuarial formulas have been shown to far outweigh clinical judgment in their ability to correctly classify people (e.g., Dawes, 1994; Meehl, 1954). Signal detection methods result in the creation of an actuarial formula in the form of an algorithm. In SDM, variables are first chosen according to theoretical interest and clinical relevance, then statistical decision making is employed to find effective combinations of variables and their cut-off points (Killen, Fortmann, Kraemer, Varady, Davis, & Newman, 1996).

Analysis of Variable Quality in Discriminating between those Able and Not Able to Quit.

Since SDM resembles a step-wise technique in that the order in which variables appear in the algorithm reflects their ability to explain the outcome behavior, SDM is able to reveal which variables are relatively stronger and weaker in predicting the outcome.

Usefulness of SDM in Relationship to other Statistical Methods. Another contribution of signal detection is its ability to handle large numbers of variables efficiently and allow for an easier interpretation of higher order interactions than general linear model methods (Williams & Flora, 1997). SDM can help clarify how variables may combine or interact

to enhance or decrease the probability of smoking cessation. Not only are interactions among variables revealed, but the specific levels above which the variables are most effective in combination with other variables can be better understood (King, et al., 1997). Unlike general linear model techniques, SDM does not require that data be linear (King, et al., 1997). This is useful when applied to the Transtheoretical model, because certain variables such as the pros, cons, and processes often do not follow a linear pattern across stages (e.g. Prochaska, et al., 1994). SDM is similar to clustering techniques in that it relies on the quality of the data instead of statistical models. In this sense, SDM can be viewed as complementary to data analysis which is based on significance tests and the assumption of linearity (Norman, Velicer, Fava, & Prochaska, 1998).

Study Goals

One goal of the present study is to identify subgroups of individuals who are more likely to quit smoking than the overall sample rate and subgroups who are less likely to quit smoking. Finding the highly successful subgroups could help behavioral scientists understand what characteristics are most likely to lead to smoking cessation.

Understanding what characteristics are most likely to lead to people being unable or unwilling to quit smoking can give scientists and practitioners information about which subgroups may need extra help or more individualized interventions to succeed. Both pieces of information could be useful in intervention planning. Another goal of this study is to develop an algorithm which can be clinically useful to determine what type of intervention may be most beneficial for different subgroups of smokers. A third goal is

to determine which of the Transtheoretical model and other variables examined in this study are the strongest predictors of smoking cessation. The fourth goal is to show that signal detection can be used to determine the best cut-off points of variables to be used in interventions such as computer based Expert System Interventions. A final goal of this study is to examine what signal detection could contribute to the understanding of smoking cessation if used together with logistic regression, a more commonly used general linear model technique. The analysis in this study is exploratory and descriptive in nature. Future confirmatory analysis will be necessary in order to know the generalizability of the results of this study.

Methods

Participants

Participants were 756 volunteers recruited through newspaper advertisements in Rhode Island as part of a longitudinal study on the efficacy of four self-help smoking interventions. Eligible participants were current smokers. Of the 756 volunteers, 93 were in the Precontemplation stage of change to quit smoking, 435 were in contemplation, and 228 were in preparation at baseline. Only participants for whom outcome data (i.e. smoking status) were available at the eighteen month point were included in the analysis. This left 602 subjects of whom 74 were in the precontemplation stage, 341 were in contemplation, and 187 were in preparation. Sixty-four percent of the subjects were female, 99% were white, and average age was 43 (SD = 12 years). Sixty-eight percent of the participants were married. Eighty-nine percent of the subjects had a high school or greater level of education, and average income was in the \$15,000 - \$25,000 range. Overall descriptive statistics for the sample of 602 participants can be seen in Table 1.

Measures

Stages of Smoking Cessation. Stage of change for smoking was assessed using a staging algorithm. Participants were asked if they were seriously considering quitting in the next six months and in the next thirty days. They were also asked several questions to

assess if they had begun to change their smoking behavior. The reply format was 'yes,' 'no,' or "I don't smoke."

Smoking Decisional Balance Scale (Velicer, DiClemente, Prochaska, & Brandenburg, 1985). This 20-item scale was used to assess 10 pros and 10 cons of smoking (coefficient alpha = .88 for pros and .89 for cons). Items such as "Smoking cigarettes is pleasurable" and "My smoking affects the health of others" were assessed using a five-point response scale, with higher scores indicating greater importance placed on these items when thinking about smoking.

Smoking Abstinence Self-Efficacy (SASE). Self-efficacy for abstaining from smoking was assessed using 20 items, adapted from DiClemente, Prochaska, & Gibertini (1985). A five-point response scale asked participants to assess how confident they were that they could refrain from smoking in twenty different challenging situations. The twenty-item scale included three subscales which measured confidence to not smoke in positive social, negative affect, and craving situations. Higher scores indicated higher efficacy. The coefficient alpha is .92.

Smoking Temptation Scale (DiClemente, Prochaska, & Gibertini, 1985; Velicer, DiClemente, Rossi, & Prochaska, 1990). The Smoking Temptation scale is included within the SASE and is another measure of self-efficacy. It assesses the level of temptation in the same twenty situations as in the SASE also using a 5-point Likert scale. This scale also assessed temptation in the same three situations as confidence. These were positive social, negative affect, and craving or addictive situations. High scores

indicated a high level of temptation. The coefficient alpha is .97 (DiClemente, Prochaska, & Gibertini, 1985).

Smoking Processes of Change Scale (DiClemente & Prochaska, 1985; Prochaska, Velicer, DiClemente, & Fava, 1988). Use of the ten processes of change was evaluated using this 40-item measure with four items for each process. Participants indicated the frequency of each of the forty situations described in the last month on a five-point Likert scale. A higher score indicated greater use of the particular process. Reliabilities of the ten processes ranged from .69 to .92.

Perceived Stress Scale. How much perceived stress subjects have experienced within the past month was assessed using this 4-item scale adapted from a 14-item measure developed by Cohen, Kamarch, & Mermelstein (1983). The short form was validated by Cohen & Williamson (1987). This scale measures the degree to which situations in an individual's life are appraised as stressful. The coefficient alpha is .72 (Cohen, Kamarch, & Mermelstein, 1983). Items such as "In the last month how often have you felt confident about your ability to handle your personal problems?" using a five-point response scale asked participants to assess how often in the past month they have had stressful experiences or feelings. Higher scores indicated lower levels of perceived stress.

Fagerstrom Tolerance Questionnaire (FTQ; Fagerstrom, 1978; Fagerstrom & Schneider, 1989). This 6-item scale, revised from the 8-item original, uses behavioral observations to measure dependence on nicotine. Items that ask about the smoking habit, such as "How soon after waking up do you smoke your first cigarette?" are combined to

create a measure of addiction. The coefficient alpha is .56 (Payne, Smith, McCracken, McSherry, & Antony, 1994).

Demographic Questionnaire. Demographic data such as age, gender, ethnicity, level of education, and income were collected.

Intervention Type. Participants in this study were assigned to one of four smoking cessation self-help interventions. Description of the interventions and how they were delivered follows:

Intervention 1: Standardized condition. A standardized treatment program was created based on materials already available in the field. In this treatment, subjects were mailed materials previously developed by the American Lung Association (ALA) and the American Cancer Society (ACS). These included three manuals: *Freedom from Smoking in 20 Days*, by the ALA which was oriented toward people attempting to quit; *A Lifetime of Freedom from Smoking*, a manual by the ALA designed to help people maintain smoking cessation; and *50 Most Often Asked Questions . . .*, an informational booklet by ACS. These materials were a combination of manuals designed for people in pre- and post-action stages. Participants also received a letter explaining each manual and the stage of change for which it was most appropriate. Participants were then encouraged to use the manuals they believed were most appropriate for them.

Intervention 2: Individualized Condition. For the individualized condition, five manuals were developed and tested based on the stages of change. The five manuals were *Precontemplation*, *Contemplation*, *Action*, *Maintenance*, and *Relapse*. Each manual explains to readers about their particular stage of change and gives stage-appropriate

advice to assist readers in moving forward through the stages. The advice includes topics such as processes, weighing pros and cons, and increasing self-efficacy.

At the first intervention point, participants were sent the manual appropriate for their stage of change and all manuals for subsequent stages. Participants who relapsed from a post-action to a pre-action stage during either the one month or six month assessments were sent the *Relapse* manual.

Intervention 3: Expert System Interactive Computer Reports Condition. In addition to the stage matched manuals, participants in this treatment received personalized interactive computer reports at the one and six month assessment points. The reports were interactive in that each participant's report was based on his or her particular responses to the questionnaires. Feedback was given regarding stage, pros and cons, and self-efficacy. The reports specified which constructs the participants were using well, and which they should use more to help them move through the stages of change. They also referred participants to particular parts of their manuals for further information. The first set of reports gave participants normative feedback, comparing participants to others who had successfully moved through their current stage. The second set of reports gave normative as well as ipsitive feedback, which let participants know how well they were using the various constructs in comparison to their first assessment point.

Intervention 4: Personal Counselor Calls Condition. In addition to the manuals in the individualized condition and the feedback reports in the personalized condition, these subjects also received proactive counselor calls at baseline, 1, 3, and 6 months. The calls

were performed by doctoral level clinical psychology students and supervised by Ph.D. level clinicians. The counselors reviewed the feedback reports with participants and gave them positive reinforcement for areas in which they were doing well and offered them support to do well in other areas. Counselors were also allowed to discuss stressful events in participants' lives if these stressors were barriers that were hindering the participants from moving through the stages of change. The calls were about 15 minutes in duration.

Outcome

Point Prevalence Abstinence. Point Prevalence abstinence (e.g. Velicer, Prochaska, Rossi, & Snow, 1992) at eighteen months after baseline was used to dichotomize smokers and non-smokers. Participants were asked through mailed follow-ups whether or not they are currently smoking. Participants who did not return questionnaires were contacted by telephone. At the six month time point, 11% of the sample had quit smoking. At the eighteen month time point, 18% of the sample had quit smoking.

Procedures

Participants called in response to newspaper advertisements. They were asked staging questions to determine their eligibility and then were randomly assigned by stage to one of four self-help smoking cessation treatment conditions. An equal number of participants from each stage were assigned to each intervention. Participants were told that they would be receiving questionnaires immediately, and then in one, six, twelve, and eighteen months. They would be paid \$5 for completing questionnaires and would

be entered into a drawing for one of ten bonus prizes for \$2,000 at each data collection point. Participants were then mailed the pretests and told they would be sent materials when they returned the questionnaires. At all data collection points, participants who did not return questionnaires within two weeks were mailed a postcard to remind them. Those who still did not return the questionnaire were called by telephone the following week and given a short form of the assessment. These participants were still encouraged to return the long form of the questionnaire by mail. Participants in the standardized and individualized manuals conditions were sent all intervention materials at baseline (except for relapsers, who were sent an extra manual at the one or six month assessment time point). Participants in the other two conditions received intervention materials at baseline and one and six months. Outcome assessment examined in this study took place one year following the six-month intervention point.

ANALYSIS

This project was a secondary analysis of the data. Signal detection methodology as adapted for the behavioral sciences (Kraemer, 1988) was used to create an algorithm which is optimally efficient at discriminating those who have quit smoking from those who have not. This study was exploratory in nature. Following is a brief overview of signal detection in its traditional form using smoking cessation as an example to help clarify certain points. Secondly, a description of how the method has been adapted for the behavioral sciences will be presented. Then, literature using signal detection for the behavioral sciences will be reviewed briefly. Terms necessary to understanding the analysis will be defined. Finally, a step-by-step explanation of how signal detection analysis was run will be presented.

Overview of Signal Detection

Signal detection methods assess a decision makers' ability to discriminate between two dichotomous choices. In the case of smoking cessation, the decision makers are the independent variables and the dichotomous choice is a smoking versus non-smoking condition at 1-year follow-up. Within the structure of SDM, the variables are seen as tests that are assessed for their ability to discriminate smokers from non-smokers. Better quality tests are better able to discriminate (Kraemer, 1988).

SDM can assess three aspects of a test's quality: sensitivity, specificity, and efficiency. Sensitivity is the ability of a test to find a condition when the condition is present (this is called a hit or a true positive). Specificity is the test's ability to decide that a condition is not present when it is actually not present (this is called a correct

rejection or a true negative) (Kraemer, 1988). Efficiency is a test's ability to classify the most number of people correctly by maximizing true positives and minimizing true negatives (Kraemer, 1992). SDM accomplishes the appraisal of sensitivity and specificity by the use of a two by two matrix which contains four conditional probabilities. These are:

$P(S | s)$: The probability that the test will diagnose a person as a smoker given that the person is a smoker. This is called a hit or a true positive.

$P(S | ns)$: The probability that the test will diagnose the person as a smoker given that the person is a nonsmoker. This is called a false alarm or a false positive.

$P(NS | ns)$: The probability that the test will give a diagnosis of non-smoker given that the person is a nonsmoker. This is a correct rejection or a true negative.

$P(NS | s)$: The probability that the test will give a diagnosis of non-smoker given that the person is a smoker. This is a miss or a false negative.

Sensitivity is $P(S | s)$ and specificity is $P(NS | ns)$.

Decision making involves setting a decision rule or criterion (McNichol, 1972).

In the case of smoking cessation, this rule is a cut-off point. For example, the test variable in the smoking example can be a measure of the pros of smoking, which are measured by ten questions rated on a 1 to 5 Likert scale, with higher numbers

representing higher endorsement of the pros. Using summated scoring, the test's cut off point can be set at any point between 10 (if a subject answers are all 1's) and 50 (if the subject answers are all 5's). For example, if the cut-off is set at 35, a score of 34 or lower on the pros scale would classify someone as a non-smoker, while a score of 35 or higher would classify someone as a smoker. The four conditional probabilities and how they relate to decision rules can be summarized in a 2x2 matrix as seen in Table 2. Each row in the matrix adds to one. Thus, $P(S|s) + P(NS|s) = 1$ and $P(NS|ns) + P(S|ns) = 1$. In this way, signal detection breaks down decision making into two independent probabilities. There is the probability of classifying someone correctly or incorrectly given that the person is a smoker. The other is the probability that the test will classify someone correctly or incorrectly given that the person is not a smoker.

Cut-off points can be set to maximize sensitivity, specificity, or efficiency. Efficiency is the cut-off point where sensitivity and specificity are at their highest in respect to each other. Thus, efficiency is chosen to maximize the probability of correctly classifying the most people. The example of the 'pros' variable which has a range of 10 to 50 can be used as an illustration. Setting the cut-off point at 45 would most likely result in classifying most nonsmokers correctly, because most nonsmokers would probably have a summated pros score below 45. This test would be highly specific. However, many smokers are also likely to have a summated pros score less than 45. These smokers would all be misclassified as non-smokers, so the test's sensitivity at this cut-off would not be very good. On the other hand, to maximize sensitivity, one would set the cut-off very low, for example at 10. This may correctly classify most smokers

who perceive higher importance of the pros of smoking than 10, but may misclassify a larger number of non-smokers who also happen to have higher awareness of the pros of smoking than a score of 10. To maximize efficiency, one would choose the cut-off point that gives the highest possible level of specificity and sensitivity relative to each other. For example, setting the cut-off at 20 may correctly classify fewer smokers than a low cut-off of 10 and fewer non-smokers than a high cut-off of 45, but there would also be fewer people misclassified in both groups. In this way, efficiency maximizes true positives and negatives while minimizing false positives and negatives.

The task of setting the cut-off should reflect the particular decision task. For example, in a case of mammography screenings, it is usually set very high, so that although there are a lot of false positives, few true positives are missed (Swets, 1992). In this case, a highly sensitive cut-off is chosen. On the other hand, our justice system is set up with a very low cut-off point. This can be evidenced in the statement, "We would rather have a hundred guilty men go free rather than have one innocent man be found guilty." In the case of our justice system, the cut-off is set to maximize specificity. For smoking cessation, the most efficient point appears to be the best decision criterion, since it optimizes true positives and minimizes false negatives. Efficiency was chosen as the rule by which cut-off points were chosen in this study. In this way, the number of people classified correctly was maximized and the number of people misclassified was minimized.

Adaptations of Traditional SDM for Behavioral Sciences

Psychology adopted SDM from the military. The method was initially used during World War II to assess human performance in military monitoring of sonar and radar detectors (Swets & Green, 1978). Psychologists' early use of this technique was in the area of visual detection (e.g. Tanner & Swets, 1954). In this case, the researcher would flash a weak signal surrounded by noise to a participant who would report whether the signal was present or not. SDM was first used in the area of medical diagnosis in the late 1960's. One way in which it has been used in the medical field has been to evaluate the accuracy of diagnostic tests (Swets & Green, 1978). In the early 1990's, SDM entered into behavioral research, such as smoking cessation and exercise adoption (e.g. Killen, et al, 1992; Killen, et al, 1996; King, et al, 1997).

SDM has been used for multiple purposes and in multiple arenas in which the underlying assumptions have varied widely. Kraemer (1988) found that many of the assumptions of the original perception model, which she calls the engineering model, are not met when SDM is used in the biological and behavioral sciences. She further points out that SDM is not robust to these violations. For these reasons, she has modified the engineering model to the behavioral model, which is more appropriate for some of SDM's current uses.

There are several differences between the two uses of signal detection that deem the adaptation of the behavioral model necessary. First, in the engineering model, scientists know the outcome with certainty since they control the signal. This would be

the equivalent of the researcher controlling whether or not the subject is a smoker.

Because the researcher does not control whether the subject quits smoking or not, the outcome itself must be measured by a test, which in this case is the question, "Are you currently smoking?" Since this question is a test, it itself will incur some level of false positives and false negatives. For these reasons, the outcome (or diagnosis) in this case is not completely certain as in the engineering model. Another difference is that in the engineering model, if one moves from one population to another, the sensitivity and specificity do not change, whereas in biological and behavioral sciences, they are population specific. Therefore, if one estimated sensitivity in one high risk population, and specificity in a low risk population, the estimated sensitivity may not be valid for the low risk population and vice-versa. For example, smoking prevalence in a cancer ward may be quite higher than smoking prevalence in a general population.

Kraemer's alternative is a partitioning method, where a series of tests are examined through SDM to find the combination that is best able to predict outcome. As in the traditional model, the researcher can determine whether this combination of tests maximizes sensitivity, specificity, or efficiency. The end result is an algorithm consisting of a series of simple 'and/or' decision rules which define groups of distinct people that are mutually exclusive and maximally discriminated from each other with respect to the dichotomous outcome (King, et al., 1997). Thus, this method is able to identify the combination of tests best able to differentiate groups of people who are able to quit smoking from those who do not quit.

Review of Literature Using Kraemer's adaptation of SDM

Research using SDM as adapted for the behavioral sciences is still sparse in the literature. Killen et al. (1992) used SDM to predict smoking relapse one year after an intervention using behavioral and pharmacological approaches. They found level of addiction to be most predictive of relapse. Their analysis revealed three subgroups that had particularly low levels of relapse. Killen, et al. (1996) looked at smoking relapse using SDM at two-year follow-up and found a relationship between depression symptoms and nicotine dependence. Their algorithm revealed that among participants whose depression symptoms decreased over the two years, lower level of nicotine dependence was associated with lower levels of relapse. For those participants whose depression level increased, gaining weight was associated with high levels of relapse.

King et al. (1997) used SDM to identify the best combinations of predictors of exercise adherence at two-year follow-up in older adults. They found that less educated participants who were assigned to home-based exercise and who were also less stressed and less fit at baseline were the most likely to adhere. Least likely to adhere were overweight individuals assigned to group-based exercise. Wilcox and King (1997) applied SDM to identify subgroups of individuals who prefer home- versus class-based exercise programs. They found that most people preferred home-based programs, but that preferences varied according to selected demographic, health, and psychosocial variables. Finally, Williams and Flora (1997) used SDM to identify subgroups of Hispanics at risk for cardiovascular disease that could require unique campaign planning

strategies. They found six distinct subgroups that differed in communication, behavioral, psychological, and demographic variables.

Defining Terms

Several more terms need to be defined in order to understand signal detection for the behavioral sciences. Most of these terms are best understood in relation to the two by two decision making matrix in Table 2.

For any condition, there is a prevalence rate (P) within a given population.

Prevalence, or P, is the total of true positives plus false negatives found by any given test.

$$P = TP + FN$$

Prevalence can be understood as the probability of a condition existing in a population.

The level of a test (Q) is the probability that a test will have a positive result in a population. Level is all true positives plus all false positives.

$$Q = TP + FP$$

Sensitivity and specificity have already been defined as conditional probabilities describing test performance with reference to a diagnosis. Sensitivity (SE) is the probability of test being positive when a condition exists and specificity (SP) is the probability of a test being negative when a condition does not exist. Generally, as one increases, the other decreases. The two constructs can also be understood as:

$$SE = TP/P$$

$$SP = TN/(1-P)$$

Similar to sensitivity and specificity are predictive values of a test. These are conditional probabilities describing the performance of a diagnosis with reference to a test. Predictive value of a positive test (PVP) is the probability of having a positive diagnosis among subjects who have a positive test. Predictive value of a negative test (PVN) is the probability of having a negative diagnosis among subjects who have a negative test.

$$PVP = TP/Q$$

$$PVN = TN/(1-Q)$$

Tests that optimize sensitivity also optimize PVP. Tests that optimize specificity also optimize PVN (Kraemer, 1992).

Efficiency (EFF) is the cut-off point which has the highest level of true positives relative to the lowest level of true negatives (Kraemer, 1992). Thus, efficiency is chosen to maximize the probability of correctly classifying the most people.

$$EFF = TP + TN$$

Tests will be defined as every independent variable included in the signal detection analysis at every possible cut-off point. Thus, the variable pros (which has a range of 10 to 50) is not one test, but 40 tests, such that the test of pros greater than or equal to 36 is a separate test from pros greater than or equal to 37, and so on.

Applying SDM in the Present Study

The Tree Diagram Algorithm - A Mathematical Way of Evaluating Test Quality

To run SDM for smoking cessation, the most efficient cut-off points for all of the variables were found. This was done using the QROC program developed by Kraemer (1992). For each variable, at each possible cut-off point, Chi square tests were run on the data available in the 2x2 matrix of test and diagnosis described earlier (see Table 2). The test with the highest chi-square value of all of the variables at every possible cut-off point was considered the best test.

Based on the cut-off value of this test, the sample was then split into two groups, those who were positive and those who were negative on this test. The significance level was set at $p < .05$. Thus, tests that were not significant at this level were not considered good tests. Two subgroups (test positive and test negative) now existed which were mutually exclusive and maximally discriminated from each other based on the most efficient cut-off of the first test. For each subgroup, the chi-square test was then run again on the remaining variables at all possible cut-off points. Splitting was continued until one of two possibilities occurred. Either, splitting ceased if the marginal count of the cut-offs for variables fell below ten subjects. Or, splitting ceased when there were no longer variables left which were significant at a .05 level (Kraemer, 1992).

For each test chosen by the signal detection methods as a good test, the positive predictive power of the test was reported. Since two subgroups had been created by the

test (those who were test positive and those who were test negative), PVP was reported for both groups. A good test should report a PVP higher than the base rate for smoking cessation for the overall sample (18% at eighteen months and 11% at six months) for the group positive on the test and a PVP rate lower than the base rate of eighteen for those subjects who had negative test results. This shows that the test is better able to discriminate smokers from nonsmokers than base rates (Kraemer, 1992).

ROC and QROC Curves - A Geometric Approach to evaluating Test Quality

ROC Curves In signal detection, each test under consideration can be located on a graph of sensitivity (probability of a positive test when there is a positive diagnosis) on the y-axis versus specificity (probability of a negative test when there is a negative diagnosis) on the x-axis. This graph is known as the Receiver Operating Characteristic, or ROC. An example of a ROC curve can be seen in Figure 1. What is seen is an arc lying above the diagonal line and extending from the lower right to the upper left hand corner of the graph. This arc represents all of the possible cut-off points of a signal detection test converted to a scale from 0 to 1. The diagonal line represents the form the ROC curve would take if the false positive rate of the test was equal to the false negative rate, i.e. if the test's ability to classify people was no better than chance (McNichol, 1972; Swets and Green, 1978). This line is called the random ROC. Tests with high specificity would be located further to the right on the ROC curve, while tests with higher sensitivity

would be located closer to the left on the scale but above the random ROC line (Kraemer, 1992).

When a number of tests are being evaluated, as in the present study, a ROC in the form of a 'Test Family ROC' may be used (Kraemer, 1992). In the Test Family ROC, each test is plotted against the sensitivity and specificity at an already identified cut-off point. All cut-off points should be chosen with a common decision rule, i.e. to maximize sensitivity, specificity, or efficiency. When several tests are plotted against each other in this way, they will most likely not all fall on the ROC curve. The ROC curve is formed by connecting the tests furthest to the outside of the graph. The tests that fall on the ROC curve which are also nearest to the right hand corner of the graph are the optimal tests. These tests are optimal because they appear to have both greater sensitivity and specificity than tests that lie in the area between the ROC curve and the diagonal. Thus, a test which falls on the ROC curve would be preferable to one which lies within the area. Figure 2 shows a sample test family ROC.

A criticism of the ROC curve's ability to identify a best test is that a test's location on the curve may be misleading as to its quality. For example, a test may be located far to the left on the ROC curve, which would indicate that it has high sensitivity. However, the test may also be in this position because the test has a high level (Q), or a high probability of coming up positive. This is also true for a test which is located far to the right on a ROC curve. It may be a high quality test for predicting specificity, but it may also just have a high rate of negative outcomes. There are many reasons why tests may have a high positive rate that do not necessarily mean that the results are accurate.

Thus, sensitivity and specificity do not necessarily reflect a test's quality (Kraemer, 1992).

QROC Curve. Kraemer (1988, 1992) suggests an alternative method to plotting the test points than the traditional ROC curve. She calls this method the Quality Receiver Operating Characteristic or QROC. In the QROC, every test is located on a graph according to its test quality, which is measured by its kappa coefficient. On the y-axis, quality is assessed by the kappa coefficient of sensitivity which is sensitivity minus the test's level (Q) divided by Q'. On the x-axis, quality is assessed by the kappa coefficient of specificity minus Q' divided by Q. In other words,

$$QI (1,0) = (SE - Q)/(Q') \text{ and}$$

$$QI (0,0) = (SP - Q')/(Q),$$

where QI is defined as quality.

The random QROC (at which point a test would not perform better than chance) is the point (0,0), so all of the tests included for analysis will lie above that point. The (0,0) point can be seen as a null test, since it is not significantly different from chance. All of the outermost tests are connected to each other stemming from and returning to the null test or (0,0) point. A leaf like figure emerges. Figure 3 shows an example of a hypothetical QROC graph. The benefits of the QROC over the ROC for selecting a best test is that it becomes much easier to identify the tests with the optimal sensitivity, specificity, and efficiency. The test furthest to the bottom right is the test which is optimally specific, the one furthest to the top left is optimally sensitive, and the test closest to the ideal point is the most optimally efficient. Tests which simply have a high

probability of being positive or negative are no longer affecting the results, so the test quality becomes easier to interpret.

To summarize, the following are how tests are evaluated for quality using ROC and QROC curves.

1. If a test is on the random ROC or QROC, it is not a good test, because it does not predict outcome better than chance.
2. If a test is in between the random ROC or QROC and the ROC or QROC curve, it is not a best test, because there are tests on the curve which are better predictors of outcome.
3. If a test is on the ROC curve, it may be a good test, but it may not be much better than random if it simply has a high rate of positive diagnoses.
4. If a test is located on the QROC, tests between the optimally efficient and optimally specific tests are good tests.

For each test found to be a good test by signal detection methods, QROC diagrams were developed to demonstrate visually why this test was selected as the best test from among other tests. In the first study, a ROC diagram will also shown to demonstrate that QROC diagrams are easier to read.

Correlation of Variable and Outcome

The correlation of an independent variable to a dichotomous outcome variable is called a point biserial correlation coefficient (Kraemer, 1992). This correlation coefficient is an indication of the overall value of a test in predicting the outcome. The

magnitude of the coefficient is proportional to the area under the ROC curve. Thus, the greater the value of the coefficient, the further will the variable be located toward the ideal point (upper right hand corner) on the ROC graph. The point biserial correlation coefficient of the entire sample for each variable entered into the analysis was reported to help assess the overall quality of the baseline variables in predicting smoking cessation eighteen months later. The correlations of variable to outcome vary for subsamples with different characteristics. Only point biserial correlations for the entire sample (not subsamples) were reported here.

Missing Data

Missing data in the signal detection analysis was handled in the following way. Subjects for whom the outcome data is missing were eliminated from the analysis. If subjects were missing data from a predictor variable, they were omitted from all analyses which include that variable, but included in all other analyses where data were not missing.

Logistic Regression

Logistic regression was also run on the data to see which variables would be found to be significant predictors of smoking cessation using a general linear model method. Significance was set to $p < .05$, but variables which were significant at the $p < .2$ level were also reported so that meaningful information was not lost because of

possible confounding of variables (Lang, 1998). This allowed for an analysis of some differences between signal detection and a general linear model technique. Subjects for whom data were missing were excluded from the logistic regression analysis.

Studies 1 and 2

Two signal detection studies were run using smoking cessation at eighteen months as the outcome variable. The difference in the two studies were that in each one certain variables were operationalized in different ways. In Study 1, the variables stage and intervention were entered as dummied variables, while in Study 2, they were entered as ordinal variables. In study 1, processes of change were entered as ten variables, each representing one of the processes of change, while in Study 2, they were entered as two variables, for the two higher order factors of experiential and behavioral processes of change. Finally, in Study 1, self-efficacy was examined as two variables, confidence to not smoke and temptation to smoke. In Study 2, self-efficacy was examined as three variables which were confidence to not smoke when experiencing negative affect, confidence to not smoke when in positive social situations, and confidence to not smoke when experiencing cravings. The point of running two separate analyses was to see the impact of identifying variables differently on the outcome of the methodology. For both studies, preliminary algorithms were developed, then bad tests were excluded to form a final algorithm. Bad tests were considered to be ones in which both subgroups identified by the cut-off level tested either above or below the prevalence level. For example, 18%

of subjects were able to quit smoking at the eighteen month point. A test which is split into two groups, one in which 35% of subjects were able to quit and one in which 45% of subjects quit, is not a good test, because it does not discriminate between those more likely and less likely than the prevalence rate to quit. Final algorithms were developed which excluded all bad tests. Results of running this data through logistic regression analysis are presented for both studies.

Study 3: Six Month Outcome

In this study signal detection methods were used to identify the best tests for predicting smoking cessation at six months following baseline. Variables were operationalized in the exact same way as in Study 2. The objective of Study 3 was to assess the differences in best tests at six and eighteen months. Only the final algorithm developed using the signal detection methods and correlations between predictor variables and outcome are reported.

Study 4: Cut-Offs by Stage

In a fourth sub-study, Transtheoretical model variables including pros, cons, self-efficacy, temptation, and the ten processes of change were tested against outcome by stage. In this way, most efficient cut-off points to predict smoking cessation were

determined. This method could be used to determine cut-off points for Expert System interventions. However, this study was preliminary because it did not look at predicting forward stage movement, which is the goal of Expert system interventions. Rather it looked at predicting movement into the action or maintenance stages eighteen months later. This sub-study is still useful to demonstrate the ability of signal detection to use a methodological approach to develop clinically useful decision rules.

Results

STUDY 1

Methods for Study 1

To predict smoking cessation at eighteen-month follow-up, the following baseline variables were evaluated simultaneously using signal detection methodology: sex, age, income, years of education, type of intervention (1,2,3, or 4), baseline stage of change (precontemplation, contemplation, or preparation), level of addiction, perceived stress, pros, cons, confidence to not smoke, temptation to smoke, and the ten processes of change (counterconditioning, consciousness raising, dramatic relief, environmental reevaluation, helping relationships, reinforcement management, stimulus control, self-liberation, social liberation, and self-reevaluation). The ranges of the predictor variables included in Study 1 can be seen in Table 3. All variables were tested in increments of 1. For example, the pros variable had a value ranging from ten to fifty. This means those who scored ten were tested against those who scored eleven to fifty, then those who scored ten or eleven were tested against those who scored twelve to fifty, and so forth. Ethnicity was not evaluated as a test in this study because 98% of the study population was white.

Test responses which were ordinal were entered in an ordinal scale. Dummy variables were created for categorical variables. A dummy variable was created for each of the four interventions and the three stages of change. Subject scores were entered as a

1 if they belonged to a certain intervention or stage, and marked as zeros for all interventions and stages to which they did not belong.

Results for Study 1

Correlation with Outcome

The point biserial correlation of each independent variable with the outcome variable of smoking cessation using the entire sample of smokers can be seen in Table 3. This correlation coefficient is an indication of the overall value of a variable in predicting the outcome and is proportional to the area under the ROC curve.

Algorithm and QROC

The results of the algorithm for study 1 are shown in the tree diagram in Figures 4 and 5. Overall, 18% of the sample had quit smoking at eighteen month follow-up. The initial best test found by the QROC program was perceived stress. Participants who had very low perceived stress were more likely to quit smoking than were those with higher stress levels (52% PVP of participants with perceived stress scores equal to 20 compared to 17% PVP of those with perceived stress scores less than 20 where higher scores indicated less perceived stress) $\chi^2(1, N = 601) = 21.64, p < .001$.

Figure 6 shows the ROC curve results for the first signal detection run for this analysis. Although signal detection methods found perceived stress to be the best test, this is not clear from looking at the ROC curve. Although the variable stress is located

on the ROC curve, so are numerous other variables. It is not clear from simply looking at this graph which test would be chosen as most efficient, sensitive, or specific. Variables can appear on the curve several times. This is because these variables were found to be good tests at several cut-off points. All of these points are plotted on the graph. Figure 7 shows the QROC curve for the same set of data. In this figure, perceived stress clearly stands out furthest toward the ideal point on the graph. Because the QROC is easier to interpret than the ROC, only the QROC will be reported in the rest of this analysis.

Among individuals with very low stress levels, those who believe the pros of smoking to be low were more likely to quit than those who believed there were more benefits to smoking (80% with Pros scores equal to or lower than 22 versus 35% with pros scores higher than 22) $\chi^2(1, N = 24) = 5.04, p < .05$. Figure 8 shows the QROC results for this run. Pros stand out furthest to the upper right hand corner of the graph. Marginal counts were not large enough to continue splitting this subgroup.

Among individuals with higher perceived stress, those who were using the process of Self-reevaluation more were more likely to have quit smoking than those who were using this process less (28% of participants with Self-reevaluation scores of 19 or higher compared to 15% of participants with scores lower than 19) $\chi^2(1, N = 577) = 8.58, p < .01$. The QROC plot for this test can be seen in Figure 9. From this figure, it is difficult to determine whether Self-reevaluation or Addiction is the best test. However, the chi-square value for Self-reevaluation ($= 8.58$) is much higher than chi-square value for addiction ($= 4.98$). It should still be noted that the chi-square value for addiction is significant at the .05 level.

As can be seen in Figures 4 and 5, the recursive partitioning split the sample of subjects with higher stress scores and higher Self-reevaluation scores three more times. Fifty percent of those who perceived the cons of smoking to be high (greater than or equal to 48) were able to quit smoking, as opposed to 19% of those with cons scores lower than 48, $\chi^2(1, N = 78) = 7.56, p < .05$. Figure 10 shows the QROC for the cons variable. Of those with Cons scores greater than or equal to 48, subjects with consciousness raising scores equal to or lower than 17 were more likely to quit smoking than those who reported using this process more (71% of subjects with consciousness raising scores equal to or lower than 17, as opposed to 20% of others), $\chi^2(1, N = 24) = 6.17, p < .05$. See Figure 11 for the QROC graph for this sub-test. Among those subjects with more stress and more use of the Self-reevaluation process who had cons scores lower than 48, those aged 44 or older were more likely to quit smoking than younger subjects (44% of those age 44 or older as opposed to 7% of younger subjects), $\chi^2(1, N = 52) = 9.35, p < .01$. Figure 12 shows the QROC for this test. Neither the subgroup which split on age nor the subgroup that split on use of consciousness raising could be divided further because the marginal cell counts were not large enough.

The sub-sample of people with higher perceived stress and lower use of the self-reevaluation process were partitioned again based on how tempted they were to smoke in various situations. Twenty-four percent of those who were less tempted to smoke were able to quit as opposed to only 12% of those who were more tempted (those with temptation scores less than or equal to 68 were more likely to quit), $\chi^2(1, N = 478) = 12.04, p < .001$. (See Figure 13 for QROC.) The recursive partitioning rule allowed the

sub-sample with less temptation to smoke to be split one more time. Those subjects who made greater use of the dramatic relief process were more likely to quit than those who made less use of this process (67% of those who had dramatic relief scores equal to or greater than 17, as opposed to 20% of those with scores below 17) $\chi^2(1, N = 129) = 12.77, p < .001$. (See Figure 14 for QROC.) Splitting for this subgroup was stopped here because the marginal cell count was too small.

Several more splits occurred among those subjects with more perceived stress, less use of self-reevaluation, and higher temptation to smoke. Subjects less likely to use the process of consciousness raising (consciousness raising score equal to or less than 8) were more likely to quit smoking (21% were able to quit as opposed to 9% of those with consciousness raising scores greater than 8) $\chi^2(1, N = 331) = 6.98, p < .01$. (See Figure 15 for QROC.) Splitting stopped for the subgroup with less use of consciousness raising because no further splits were found to be statistically significant.

Among the subgroup with greater use of consciousness raising, subjects who perceived the pros of smoking to be low were more successful than subjects who perceived the pros of smoking to be higher (36% of those with pros scores less than or equal to 8 as opposed to 8% of those with scores greater than 8), $\chi^2(1, N = 266) = 9.80, p < .01$. (See Figure 16 for QROC.) The subgroup with lower perceived pros of smoking stopped splitting there because the marginal cell count was less than ten subjects.

Among subjects with higher perceived pros of smoking, those who were in the Expert Feedback intervention group were more likely to quit smoking than subjects in the other three interventions (17% as opposed to 5% in the other groups), $\chi^2(1, N = 255) =$

8.38, $p < .01$. (See Figure 17 for QROC.) The subgroup of subjects who were not in the Expert System intervention group was not split any further because no other tests were found to be significant. Those in the Expert System intervention group were split one more time. Those with fourteen or more years of education were more likely to quit than those with less than 14 years of education (29% as opposed to 6%), $\chi^2(1, N = 66) = 6.44$, $p < .05$. (See Figure 18 for QROC.) No other tests were found to be significant to further split the subsamples.

Logistic Regression

A logistic regression analysis of all of the baseline independent variables against smoking cessation outcome at eighteen months was statistically significant, $\chi^2(25) = 46.797$, $p < .01$. This model had an overall prediction rate of 71.4%. Four-hundred ninety-eight subjects were included in this analysis. Table 4 shows the regression coefficients, Wald Statistics, and odds ratios for each of the variables. Female gender ($z = 6.69$, $p < .01$) and age ($z = 5.82$, $p < .01$) were significant predictors of smoking cessation. According to this model, older subjects (odds ratio = 1.03) who were women (odds ratio = 2.21) were more likely than younger or male subjects to quit smoking. Because of the possible confounding of variables in this logistic regression, meaningful information may be lost by only reporting variables which were significant at the $p < .05$ level (Lang, 1998). For this reason, variables with p-values less than .2 were also reported. Variables significant at $p < .2$ included Intervention 3 ($z = 2.73$, odds ratio = 1.750), stage of change (Precontemplation: $z = 1.88$, odds ratio = 0.492, Contemplation: z

= 1.66, odds ratio = 0.696), stress ($z = 3.23$, odds ratio = 1.080), consciousness raising ($z = 3.37$, odds ratio = 0.921), self-reevaluation ($z = 2.45$, odds ratio = 1.081), and temptation ($z = 4.95$, odds ratio = 0.976). Using the $p < .2$ level would thus indicate that subjects who received intervention 3 were more likely to quit, those in the preparation stage were more likely to quit, along with those subjects who had less perceived stress, used consciousness raising less, self-reevaluation more, or were less tempted to smoke.

Final Algorithm Development: Getting Rid of Poor Tests

Several of the tests in this study based upon which subgroups were created predicted both subgroups to have positive outcomes either above or below the overall sample rate of 18%. These tests were pros less than or equal to 22 (where pros was located under stress positive), consciousness raising less than or equal to 17, and dramatic relief greater than or equal to 17. Tests which predict positive outcomes for both groups which are above or below the prevalence rate for the overall sample are poor tests because they are not actually discriminating between those more or less likely to succeed than the overall sample (Kraemer, 1992). For this reason, these three tests will be excluded from the final algorithm created on the basis of this analysis. The final algorithm for Study 1 can be seen in Figures 19 and 20.

Summary of Results - Study 1

As shown in Figures 19 and 20 the signal detection method identified eight subgroups of subjects on the basis of the probability of their quitting smoking. These can

be divided into six subgroups with positive outcomes (i.e. higher probability of smoking cessation than the overall sample) and two subgroups with negative outcomes (i.e. lower probability of smoking cessation than the overall sample).

Subgroup 1. Among the subgroups with positive outcomes, subgroup 1 had the highest probability of smoking cessation, 52%. Members of this subgroup were less stressed at baseline. There were eight non-smokers who fit this profile.

Subgroup 5 had the next highest probability of smoking cessation, 36%. These subjects had initially moderately low to high perceived stress, were using the process of self-reevaluation less, used consciousness raising less, and were less aware of the pros of smoking. Four non-smokers fit this profile.

Subgroup 2, which consisted of moderately low to high stress people who had high use of the self-reevaluation process, had 28% positive outcome. Twenty-two non-smokers fit this profile.

Subgroup 3 consisted of moderately low to high stress people with low use of self-reevaluation, who were less tempted to smoke. Twenty-eight percent of this subgroup was successful. Thirty-one non-smokers fit this profile.

Subgroup 4, which was more stressed, used self-reevaluation less, felt more tempted to smoke, and used consciousness raising less had a 21% chance of quitting smoking. There were thirteen nonsmokers who fit this profile.

Subgroup 5. The subgroup with the lowest negative outcome was subgroup 5, which contained 9 non-smokers and had a quit rate of 5%. Members of this subgroup were more stressed, used self-reevaluation less, felt more tempted, used more

consciousness raising, perceived more benefits to smoking, and were not in intervention group 3.

Subgroup 6 looked much like subgroup 5, except the members of this group were in intervention group 3 and had less than 14 years of education. Only 6% of these people were able to quit smoking, which was also a total of 9 non-smokers.

STUDY 2

Methods for Study 2

To predict smoking cessation at eighteen-month follow-up, the following baseline variables were evaluated simultaneously using signal detection methodology: sex, age, income, years of education, ethnicity, type of intervention (1,2,3, or 4), baseline stage of change (Precontemplation, contemplation, or preparation), level of addiction, perceived stress, pros, cons, confidence to not smoke positive social situations, confidence to not smoke when experiencing negative affect, confidence to not smoke when craving cigarettes, behavioral processes, and experiential processes. The ranges of the predictor variables included in Study 2 can be seen in Table 5. All variables were tested in increments of 1.

In this study, the three factors of confidence were tested instead of confidence and temptation as one factor each. This was done to see if using the subscales of confidence would reveal any more information than a single confidence factor. Confidence and

temptation were not both tested since the two variables are highly correlated ($r = -.595$). The processes were tested as two factors, behavioral and experiential, instead of the ten individual processes as in Study 1, to see if they would have stronger predictive power in this form. Test responses which were ordinal were entered in an ordinal scale. Dummy variables were created for categorical variables. Ordinal variables were created for intervention and stage, since each stage or intervention can be seen as a progression from the previous one. Intervention 1 was entered as level 1 of the intervention variable, intervention 2 was entered as level 2, and so forth. Precontemplation was entered as level 1 of the stage variable, contemplation was entered as level 2, and preparation was entered as level 3.

Results for Study 2

Correlation with Outcome

The point biserial correlation of each independent variable with the outcome variable of smoking cessation using the entire sample can be seen in Table 5.

Algorithm and QROC

The results of the algorithm for study 2 are shown in the tree diagram in Figures 21 and 22. Overall, 18% of the sample was successful at smoking cessation at eighteen month follow-up. The initial best test found by the QROC program was perceived stress. Participants who had very low perceived stress were more likely to quit smoking than

were those with higher stress levels (52% PVP of participants with perceived stress scores equal to 20 compared to 17% PVP of those with perceived stress scores less than 20) $\chi^2(1, N = 601) = 21.64, p < .001$.

Figure 23 shows the QROC curve for this split of the data. Several variables appear on the curve several times. This is because these variables were found to be good tests at several cut-off points. All of these points are plotted on the graph.

Among individuals with very low stress levels, those who believe the pros of smoking to be low were more likely to quit than those who believed there were more benefits to smoking (80% with Pros scores equal to or lower than 22 versus 35% with pros scores higher than 22) $\chi^2(1, N = 24) = 5.04, p < .05$. Figure 24 shows the QROC results for this run. In this QROC, both pros of smoking and type of intervention (higher success rates for those in Intervention 3 or 4) appear to be good tests. Pros was chosen as the best test because it had a higher chi-square value ($= 5.04$) than intervention ($= 4.46$). However, it should be noted that both tests were significant at the .05 level. Marginal counts were not large enough to continue splitting this subgroup.

Among individuals with higher perceived stress, those who had higher confidence to not smoke when feeling negative affect were more likely to have quit smoking than those who less confidence (32% of participants with confidence under negative affect scores of 19 or higher compared to 15% of participants with scores lower than 19) $\chi^2(1, N = 569) = 9.23, p < .01$. The QROC plot for this test can be seen in Figure 25. Among those with higher confidence to not smoke when feeling negative affect, 50% of those who had greater use of experiential processes (greater than or equal to 63) were able to

quit smoking, as opposed to 9% of those with experiential processes scores less than 63, $\chi^2(1, N = 51) = 9.28, p < .001$. Figure 26 shows the QROC for the experiential processes variable. Of those with experiential processes scores greater than or equal to 63, subjects with addiction scores equal to or lower than 4 were more likely to quit smoking than those who were more highly addicted (82% of subjects with addiction scores equal to or lower than 4, as opposed to 27% of others), $\chi^2(1, N = 24) = 7.72, p < .01$. See figure 27 for the QROC graph for this sub-test. The marginal count was not large enough to continue splitting the sample of subjects with experiential processes scores less than 63.

Among those subjects with more stress and less confidence to not smoke when feeling negative affect, those who had more confidence to not smoke in positive social situations were more likely to quit smoking (31% of those with scores greater than or equal to 19 as opposed to 14% of other subjects), $\chi^2(1, N = 518) = 8.40, p < .01$. Figure 28 shows the QROC for this test. The subgroup of subjects who had greater confidence to not smoking in positive social situations was split one more time. Those subjects who were 48 years old or older were more likely to quit than younger subjects (55% of older subjects as opposed to 23% of younger subjects), $\chi^2(1, N = 40) = 3.88, p < .05$. The QROC for this test is in Figure 29.

The sub-sample of people with higher perceived stress, lower confidence in negative affect situations and lower confidence in positive social situations were partitioned again based on how aware they were of the pros of smoking. Twenty-nine percent of those with pros scores lower than or equal to 16 were able to quit as opposed to only 13% of those who were more aware of the pros of smoking) $\chi^2(1, N = 470) = 6.61, p$

< .05. (See Figure 30 for the QROC.) The marginal count was not large enough to split the sub-sample with lower pros scores again. The recursive partitioning rule allowed the sub-sample with greater importance of the pros of smoking to be split one more time. Those subjects who were younger than 67 years old were more likely to quit than older subjects (32% of older subjects, as opposed to 12% of younger subjects) $\chi^2(1, N = 428) = 6.22, p < .05$. (See Figure 31 for QROC.) No other tests were found to be significant to further split the subsamples.

Logistic Regression

A logistic regression analysis of all of the baseline independent variables against smoking cessation outcome at eighteen months was statistically significant, $\chi^2(16) = 32.222, p < .01$. This model had an overall prediction rate of 67.0%. Five hundred and nine subjects were included in this analysis. Table 6 shows the regression coefficients, Wald Statistics, and odds ratios for each of the variables. As in Study 1, female gender ($z = 4.88, p < .05$) and age ($z = 5.84, p < .05$) were significant predictors of smoking cessation. According to this model, older subjects (odds ratio = 1.03) who were women (odds ratio = 2.21) were more likely than younger or male subjects to quit smoking. Again, because of the possible confounding of variables in this logistic regression, variables with p-values less than .2 are also reported. Variables significant at $p < .2$ include intervention ($z = 1.79, \text{odds ratio} = 1.155$), stage of change ($z = 2.99, \text{odds ratio} = 1.441$), stress ($z = 2.23, \text{odds ratio} = 1.063$), pros ($z = 2.34, \text{odds ratio} = 0.973$), cons ($z = 2.05, \text{odds ratio} = 1.030$), and ethnicity ($z = 3.13, \text{odds ratio} = 0.208$). Using the $p < .2$

level would thus indicate that subjects were more likely to quit depending on to which intervention they were assigned and in what stage they were at baseline. Also, those who were not white, had less stress, were less aware of the pros of smoking or more aware of the cons were more likely to quit.

Final Algorithm Development: Getting Rid of Poor Tests

As in Study 1, several of the tests in this study based upon which subgroups were created predicted both subgroups to have positive outcomes either above or below the overall sample rate of 18%. These tests were pros less than or equal to 22, addiction less than or equal to 4, and age greater than or equal to 48. These three tests will be excluded from the final algorithm created from this analysis. The final algorithm for Study 2 can be seen in Figures 32 and 33.

Summary of Results - Study 2

As shown in Figures 32 and 33, the signal detection method identified seven subgroups of subjects on the basis of the probability of their quitting smoking. These can be divided into five subgroups with positive outcomes (i.e. higher probability of smoking cessation than the overall sample) and two subgroups with negative outcomes (i.e. lower probability of smoking cessation than the overall sample).

Subgroup 1. Among the subgroups with positive outcomes, subgroup 1 had the highest probability of smoking cessation, 52%. These subjects had initially low perceived stress. Twelve non-smokers fit this profile.

Subgroup 2 had the next highest probability of smoking cessation, 50%.

Members of this subgroup were more stressed at baseline, had greater confidence to not smoke when feeling negative, and used experiential processes more. There were thirteen non-smokers at eighteen month follow-up who fit this profile.

Subgroup 6, which consisted of people who were more stressed, less confident when experiencing negative affect and when in positive social situations, were more aware of the pros of smoking, and younger than 67 years old, had a 32% chance of positive outcome. Seven non-smokers fit this profile.

Subgroup 4, which consisted of moderately low to high stress people who were less confident that they could refrain from smoking when experiencing negative affective but were confident they could refrain in a positive social situation had 31% positive outcome. There were also thirteen non-smokers who fit this profile.

Subgroup 5 consisted of people who were more stressed, less confident when experiencing negative affect and when in positive social situations, and were less aware of the pros of smoking. Twenty-nine percent of this subgroup was successful. Nine non-smokers also fit this profile.

Subgroup 3. The subgroup with the lowest negative outcome was subgroup 3, which contained 2 non-smokers and had a quit rate of 9%. Members of this subgroup were more stressed, more confident to not smoke when feeling negative and used the experiential processes less.

Subgroup 7. The other subgroup with negative outcome was subgroup 7. This group was more stressed, less confident in both negative affect and positive social

situations, was more aware of the pros of smoking, and was younger than 67. This group only had a 12% success rate. Forty-six non-smokers fit this profile.

STUDY 3

Methods for Study 3

Methods for Study 3 were identical to methods for Study 2, except that smoking cessation at six months was used as the outcome variable instead of smoking cessation at eighteen months. At six months, 11% of the sample (62 subjects) had quit smoking. Outcome data were available for 566 subjects, thus this many subjects were included in the analysis. The ranges of the variables included in Study 3 are the same as the ranges of the variables included in Study 2. They can be seen in Table 7. Correlation of all of the predictor variables with outcome for Study 3 can be seen in Table 10.

Summary of Results for Study 3

As can be seen in Figures 34 and 35, an initial algorithm which created eight subgroups was developed for Study 3. Income was excluded from the final algorithm for being a poor test. Cutting out income also excluded the test confidence when experiencing cravings. As can be seen in Figures 36 and 37, six subgroups were included in the final algorithm, four with higher positive outcome rates than the prevalence rate and two with a lower positive outcome rate.

Subgroup 2. The subgroup with the highest success rate, 42%, was subgroup 2. Members of this subgroup had perceived stress scores lower than twenty ($\chi^2(1, 566) = 17.25, p < .001$), had greater confidence to not smoke when feeling negative (confidence

to not smoke in negative affect ≥ 19) ($\chi^2(1, 543) = 5.62, p < .05$), and were less addicted to smoking (addiction ≤ 4) ($\chi^2(1, 54) = 10.81, p < .01$). Eight non-smokers fit this profile.

Subgroup 1. The next most positive subgroup was subgroup 1 which was those subjects who had very low perceived stress ($= 20$) ($\chi^2(1, 23) = 17.25, p < .001$). Thirty-six percent of this subgroup was able to quit smoking, which was a total of eight non-smokers.

Subgroup 5. The next most successful subgroup was subgroup 5, which were more stressed, less confident when experiencing negative affect, used behavioral processes less (< 58) ($\chi^2(1, 481) = 4.32, p < .05$), and experiential processes more (> 46) ($\chi^2(1, 358) = 4.40, p < .05$). This group had 16% positive outcome and 4 non-smokers fit this profile.

Subgroup 4. The other successful subgroup was subgroup 4 which had 13% positive outcome and contained 14 nonsmokers. This subgroup contained people who were more stressed, less confident when experiencing negative affect, and used behavioral processes more.

Subgroup 3. The two subgroups with the lowest smoking cessation rates both had a positive outcome rate of 6%. The first group, subgroup 3, was the same as subgroup 2, except with addiction scores greater than 4. Two non-smokers fit this profile.

Subgroup 6. The other subgroup with a low positive outcome was subgroup 6, which was a total of 19 non-smokers. This subgroup had higher perceived stress, lower

confidence to not smoke when feeling negative, lower use of behavioral processes and greater use of experiential processes.

STUDY 4: CUT-OFFS BY STAGE

In this sub-study, signal detection was used to determine the most efficient cut-off points for Transtheoretical model variables in each of the three stages of change. Most efficient cut-off points for the variables pros, cons, confidence, temptation, and the ten processes of change at baseline were assessed in order to determine which cut-off points best discriminated smokers from nonsmokers at eighteen months. The analyses were run separately by stage for precontemplation, contemplation, and preparation to see if the level at which use of variables were predictive of smoking cessation differed by stage.

Precontemplation

The QROC program was unable to determine any cut-off points for the Precontemplation stage because of the low number of subjects in this sample in this stage ($n = 73$). The number of subjects was too low for signal detection to be used to determine cut-offs which would be reliable. However, the point biserial correlation between the predictor variables and outcome are reported in Table 8. It is useful to look at this value because it gives some indication of the overall quality of the test (Kraemer, 1992). As with all of the point biserial correlations in this analysis, these correlations were low. However, the highest of these were the variables self-reevaluation (.196), dramatic relief (-.146), and pros (-.094). This may indicate that higher use of self-reevaluation, less use

of dramatic relief, and lower importance of the pros of smoking may be predictive of smoking cessation at eighteen months. However, because of the low number of subjects and the low correlation values in this analysis, these results should be considered with caution.

Contemplation

There were 341 subjects in the contemplation stage. Results can be seen in Table

9. Signal detection methods were able to determine cut-off scores for eight variables.

Five of these tests were found significant at the $p < .05$ level using chi-square tests as described earlier. Pros scores of less than or equal to 22 ($\chi^2 (1, N = 335) = 4.14, p < .05$), cons scores greater than or equal to 48 ($\chi^2 (1, N = 335) = 8.91, p < .01$), confidence greater than or equal to 54 ($\chi^2 (1, N = 328) = 5.06, p < .01$), dramatic relief scores greater than or equal to eighteen ($\chi^2 (1, N = 332) = 4.87, p < .05$), and self-reevaluation scores greater than or equal to 18 ($\chi^2 (1, N = 331) = 7.11, p < .01$) were the variables found to be significant predictors of outcome. In the cases where the correlation with outcome were positive, scores above the cut-off were associated with positive outcome. In the cases where the correlation with outcome was negative, scores below the cut-off were associated with positive outcome. Temptation scores ($\leq 69, \chi^2 (1, N = 329) = 3.14, p < .1$), consciousness raising ($\leq 8, \chi^2 = 341, p < .1$), and reinforcement management scores ($\geq 11, \chi^2 (1, N = 341) = 2.24, p < .1$) were also determined. However, Kraemer (1992) cautions against making use of cut-off scores that are not significant at the .05 level because of the already high probability of Type 1 errors in this analysis. Cons (.114),

dramatic relief (.106) and self-reevaluation (.119) have the highest correlation with outcome. As in the Precontemplation stage, these correlations were low.

Preparation

There were 185 subjects in the Preparation stage. Results can be seen in Table 10. Signal detection methods were able to determine maximally efficient cut-off scores for five variables. These were pros less than or equal to 19 (χ^2 (1, N = 183) = 7.83, $p < .01$), confidence greater than or equal to 59 (χ^2 (1, N = 182) = 7.19, $p < .01$), temptation less than or equal to 66 (χ^2 (1, N = 177) = 6.26, $p < .05$), consciousness raising less than or equal to eight (χ^2 (1, N = 185) = 5.42, $p < .05$) and helping relationships greater than or equal to 11 (χ^2 (1, N = 185) = 5.69, $p < .05$). Variable maximally efficient cut-off scores which were found to be significant at the $p < .1$ level were cons (≥ 44 , χ^2 (1, N = 185) = 1.02, $p < .1$), dramatic relief (≥ 20 , χ^2 (1, N = 181) = 2.01, $p < .1$), self-liberation (≥ 17 , χ^2 (1, N = 185) = 3.23, $p < .1$), social liberation (≤ 13 , χ^2 (1, N = 185) = 3.28, $p < .1$), and self-reevaluation (≥ 44 , χ^2 (1, N = 181) = 1.88, $p < .1$). Again, the usefulness of the results which were significant at the $p < .1$ level should be carefully evaluated. Pros (-.165) and temptation (-.141) are the variables most highly correlated with outcome. Once again, these correlations are low.

DISCUSSION

This study was the first application of signal detection methodology to assess variables from the Transtheoretical model. Two algorithms were developed which assessed characteristics related to smoking cessation at eighteen months using subjects' scores on baseline variables. One algorithm was developed to assess characteristics related to smoking cessation at six months using subjects' scores on baseline variables. In this section, several aspects of this study will be discussed. First, the variables which signal detection showed to be the strongest predictors of smoking cessation will be assessed. Secondly, implications of the subgroups identified by the algorithms will be discussed. Following will be a discussion of what signal detection can contribute to a general linear model technique. Signal detection's ability to find appropriate cut-offs for Transtheoretical model Expert System interventions will be assessed. Finally, limitations and implications of the current study will be discussed.

Assessing Which Variables are the Strongest Discriminators

One goal of the present study was to assess which variables were the strongest discriminators of those who were and were not able to quit smoking. Variables were selected based on existing theory and literature. The Transtheoretical model was selected as the guiding theory for this study because variables included in this model have been shown to be strong predictors of smoking cessation. Several other variables, such as addiction and perceived stress, were also included because existing literature as well as

other models of smoking cessation have shown them to be correlated with smoking cessation. Signal detection was used to make statistical decisions to find effective combinations of variables and their cut-off points. Reviewing the results of Study 1, then comparing the differences in outcome between Studies 1 and 2 and Studies 2 and 3 will help reveal which variables are the strongest discriminators of those who do and do not quit.

Results of Study 1. Perceived stress was found to be the strongest predictor of smoking cessation because it was the first variable on which the sample was split. A very large percentage (52%) of the people who were able to achieve a score equal to the cut-off on this variable were able to quit smoking. However, very few subjects were able to meet the cut-off criteria because it was so extreme. The cut-off was the lowest possible stress score.

This finding seems supportive of other research which has shown that there is a relationship between stress and smoking behavior. For example, decreases in perceived stress have led to decreases in number of cigarettes smoked per day (Cohen, Kamarck, & Mermelstein, 1983). Also, stress was found to be a significant predictor of smoking in a group of 332 urban women (Sheahan & Latimer, 1995). In a survey of smoking patterns, attitudes, and interest in quitting, people who were interested in quitting smoking have also been interested in learning about stress reduction (Lando, Pirie, Hellerstedt, & McGovern, 1991). Although recommendations have been made in other literature to assess the impact of stress interventions on smoking cessation (e.g. Weinrich, et al, 1996), there have not been any studies as of yet which have done so. The results of the present

study indicate that intervening on stress as part of a smoking cessation intervention could help increase the success rate of the intervention. Thus, a suggestion for future research is to examine this possibility.

The next variable to enter the algorithm in Study 1 was self-reevaluation. Thus, assessing how one thinks and feels about oneself as a smoker is important to quitting for certain smokers. This is consistent with past research which indicates that use of experiential processes is predictive of smoking cessation (e.g. Prochaska, DiClemente, and Norcross, 1992). However, use of the process of consciousness raising, which is also an experiential process, entered the algorithm in the other direction. Less use of this process was predictive of smoking cessation. Although use of this process has been shown to be a good predictor of smoking cessation in early stages of change, continuing to use this process for too long may lead to becoming a chronic contemplator, one who is always thinking about quitting, but never actually moves forward to changing behavior. A possible explanation for the direction of this cut-off is that the subgroup of people who had higher consciousness raising had chronic contemplators in the group.

Temptation was also shown to be a powerful predictor of smoking cessation. In this study, temptation to smoke and confidence to not smoke were examined as parts of the bigger construct of self-efficacy. The results show that temptation was a more powerful predictor of smoking cessation than confidence (which did not enter the algorithm at all). DiClemente, Prochaska, & Gibertini (1985) showed that although the two constructs were interrelated, they represented separate aspects of self-efficacy. The results of this study indicate that smoking cessation interventions which target self-

efficacy may have more impact by focusing on decreasing temptation than increasing confidence.

Lower importance of the pros of smoking was another strong predictor of smoking cessation. In the initial algorithm, 80% of those who had very low perceived stress were able to quit if they also perceived the pros of smoking to be of low importance. In the final algorithm, 36% of a certain subgroup was able to quit if they had low pros scores. These results are also consistent with other literature which has examined decisional balance for smoking (e.g. Prochaska, et al., 1994).

The next variable to enter the algorithm was intervention. Participants who received the Interactive Computer Reports intervention (Intervention 3) were most likely to quit smoking. Prochaska, DiClemente, Velicer, and Rossi (1993) using different methods of analysis on the same data analyzed in this study, also found this to be the most effective intervention.

The final variable to enter the algorithm was education. Thus, a demographic variable was a relatively weak predictor compared to the variables that entered the algorithm earlier because the earlier variables were able to discriminate a greater number of people. This is evidence that dynamic variables are better than static variables at predicting change.

One surprising result of this study was that stage of change did not enter the algorithm. Other literature has shown stage to be a strong predictor of smoking cessation. There are several reasons why this may be the case. Three of the four interventions to which subjects were randomly assigned were designed to move people through the stages

of change. Therefore eighteen months may have been too far from baseline for baseline stage of change to have an impact on outcome. Even without intervention, there is a possibility that people would change stages in an eighteen month period. Prochaska and colleagues (1993), using the same data set used in this study, showed that the rate of stage movement during the eighteen month period of their study was quite high. This was particularly correlated with type of intervention. This may be why baseline stage of change was not found to be a good discriminator of outcome eighteen months later.

Comparison of Study 1 and Study 2 Results. Study 1 and Study 2 looked at the same outcome point, eighteen months following baseline. With the exception of the variable ethnicity which was excluded from Study 1, the differences between the two studies lay mostly in how variables were operationalized. Stage and type of intervention were included in both studies. However, while in Study 1 they were entered as dummied variables, in Study 2, they were entered as ordinal variables. Stage did not appear in either algorithm as a good test for discriminating outcome at eighteen months.

Intervention 3, the Interactive Computer Reports Condition, was found to be a good discriminator of smoking cessation when allowed to enter the analysis on it's own in Study 1. However, it did not show up in Study 2 when this intervention was ordinally placed between the Individualized condition and the Personal Counselor Calls condition. These results indicate that receiving stage based interactive computer reports containing individualized feedback on Transtheoretical model constructs may be more effective in helping people succeed at smoking cessation than getting these reports and also getting calls from trained counselors. This would indicate that more intervention is not

necessarily better. Again, this supports the findings of Prochaska, DiClemente, Velicer, and Rossi (1993).

Another difference between Study 1 and Study 2 was in how self-efficacy was entered into the analysis. In Study 1, self-efficacy was entered as two unidimensional constructs, confidence and temptation. Temptation was found to be a good discriminator of outcome. In Study 2, self-efficacy was entered as a multidimensional construct. These constructs were confidence to not smoke when experiencing negative affect, when in a positive social situation, and when experiencing cravings. Confidence to not smoke when experiencing negative affect and when in social situations entered the final algorithm as good discriminators of outcome. The results of these two studies indicate that self-efficacy is a predictor of smoking cessation, regardless of how it is operationalized. The results may indicate that self-efficacy in the first two circumstances is better able to discriminate outcome at eighteen months than self-efficacy when experiencing cravings.

Processes of change were also entered differently in Study 1 than in Study 2. In Study 1, each of the ten processes was entered individually. In study 2, greater use of experiential processes as a whole was shown to be predictive of smoking cessation for certain subgroups. Again, this is consistent with past literature (e.g. Prochaska, DiClemente, and Norcross, 1992).

Other variables which were entered into both studies in the same manner appeared in both algorithms, as would be expected. Perceived stress was the first variable on which the sample was split in both studies. Pros of smoking also entered both algorithms.

In both studies, a demographic variable entered the study last, although it was not the same variable in both studies. More years of education was predictive of smoking cessation in Study 1, while being younger than 67 was predictive of smoking cessation in Study 2. This is further evidence that dynamic variables are better than static variables at predicting change.

Comparison of Study 2 and Study 3 Results Study 2 and Study 3 were identical except that outcome was measured at different time points. In Study 2, outcome was measured at six months after baseline, while in Study 3, outcome was measured at eighteen months after baseline. Only five variables entered the algorithm at the six-month point. These were stress, confidence to not smoke when experiencing negative affect, level of addiction, and behavioral and experiential processes. In both studies, stress entered as the first splitting point and confidence to not smoke when experiencing negative affect entered as the second. This indicates that self-efficacy and perceived stress are important to smoking cessation both at a more proximal and more distant time point.

Lower level of addiction was important in the short term but not the long term. This may indicate that those who are less addicted may be able to quit in a shorter amount of time. An interesting difference between the two time points was that greater use of experiential processes was predictive of smoking cessation in the long term, but less use of experiential processes was predictive of smoking cessation in the short term. Also, use of behavioral processes at baseline entered the algorithm in the short term, but not in the long term. These results indicate that use of experiential processes is predictive of

quitting smoking at a more distant time point. This is supported by findings that people in the precontemplation and contemplation stages are more likely to move forward if they use experiential processes (Prochaska, DiClemente, and Norcross, 1992). However, the people who quit in the short term should probably already have completed the cognitive work necessary to move forward toward quitting and have begun using some of the behavioral processes. The results of this study support this hypothesis, since at six months, those who used behavioral processes more and experiential processes less were more likely to quit.

Overall Results - Which Variables Are the Strongest Discriminators Several variables were found to be strong discriminators of smoking cessation in all three studies. Perceived stress and some form of self-efficacy entered each of the three final algorithms as the first two variables upon which the samples were split. This would indicate that these variables are the strongest discriminators of those entered in this study between those who are and are not able to quit smoking both in the short and long term. These results may indicate that people have overriding perceptions of the stress in their lives and their abilities to succeed in certain situations that are both long lasting and have impact upon their behavior. Fortunately, both of these variables are ones upon which behavioral scientists can intervene. Planning interventions which lower individuals' perceived stress and increase their self-efficacy to abstain from smoking may be powerful methods of increasing smoking cessation rates.

At the eighteen month outcome point, two other variables, pros and greater use of experiential processes, also entered both algorithms. It may be that these constructs

become more important to smoking cessation in the longer term. However, it may simply be that there were not enough subjects with positive outcomes at six months for these variables to have been detected as good tests by the signal detection methods. It is still important to note that teaching people to use experiential processes and to lower their perceptions of the benefits of smoking may be important methods of increasing smoking cessation rates.

Study 1 showed that receiving interactive computer reports was a powerful intervention for smoking cessation. Study 3 showed that level of addiction is a good discriminator between those who can quit smoking relatively quickly and those who can not. Study 3 also showed that those who were using behavioral processes of change were also more likely to quit smoking in the short term. Further research is necessary to assess the generalizability of these results, since they were not consistent across studies.

The prediction that stage of change would enter the algorithm was not supported by the results of this study. Some hypotheses for why this may have occurred at the eighteen month time point have already been proposed earlier in this section. Why baseline stage of change was not found to be a good test of smoking cessation at six months is difficult to interpret. Having higher self-efficacy in the earlier stages is predictive of forward stage movement (Velicer, DiClemente, Rossi, and Prochaska, 1990). Since this study only looked at subjects in early stages for smoking cessation, and self-efficacy was shown to be a good predictor of smoking cessation at six months some aspects of the stage constructs were captured in this algorithm. Again, it is possible that

there were simply not enough subjects who had positive outcome at this time point to capture all of the good tests.

Algorithm Development and Identification of Subgroups

Another goal of this study was to develop a clinically useful algorithm. The goal of the algorithm development was twofold. First, the algorithm would allow the identification of subgroups of individuals who were particularly unlikely to quit smoking. This information could be useful to target these individuals for tailored interventions, since the other interventions appear not to be working as effectively for them. Secondly, the algorithms allow for an identification of the most successful subgroups. Interventions could be planned to help the other subgroups more closely resemble the characteristics of the successful subgroups.

At eighteen months, several subgroups were identified through the algorithms which had extremely low rates of smoking cessation, far lower than the overall sample. The common characteristics of these subgroups were lower self-efficacy to not smoke at baseline, lower use of experiential processes (although this was predictive of shorter term cessation for people who were also using behavioral processes more), greater importance of the pros of smoking, and possibly which type of intervention they received. If future confirmatory analysis replicate these findings, it may be worth while to target these subgroups for specially tailored interventions. The algorithm developed in this study can be used to identify these subgroups.

At six months, the people who were least likely to quit smoking were the people who were more addicted even though they had higher self-efficacy and the people who were less confident, used behavioral processes less, and experiential processes more. These people sound like early stage people for whom Transtheoretical model based interventions are probably appropriate. They are simply not yet in a preparation or late contemplation stage where they are ready to take action in the near future. Interventions based on the Transtheoretical model would help these people raise their self-efficacy, move through the use of experiential processes, and begin to use behavioral processes more. Thus, the findings of the six month algorithm support the use of interventions based on the Transtheoretical model.

Assessing Signal Detection's Contribution to the Understanding of Smoking Cessation

Another goal of the current study was to assess ways in which an exploratory and relatively new method such as signal detection for the behavioral sciences could contribute to a more commonly used general linear model method to further behavioral scientists' understanding of smoking cessation. Logistic regression was chosen as the general linear model technique to be used in this analysis because, like signal detection, it predicts a dichotomous outcome. Comparison of the signal detection and logistic regression results in Studies 1 and 2 can help highlight some of signal detection's potential contributions.

Comparisons of Studies 1 and 2 with Logistic Regression Results As predicted by Kraemer (1992), the signal detection and logistic regression results were not totally

consistent with each other. In Study 1, both methods of analysis showed perceived stress, self-reevaluation, consciousness raising, self-efficacy, and Intervention 3 to be significant predictors of smoking cessation (using the .2 significance level for logistic regression). However, the logistic regression also showed stage of change, sex, age, and addiction to be significant predictors. Signal detection methods did not recognize these to be good tests for discriminating outcome. However, pros and education were not found to be significant.

In Study 2, the two methods agreed on the variables intervention, perceived stress, and pros. Logistic regression methods also found stage of change, sex, age, ethnicity, and cons to be significant predictors of outcome. However, self-efficacy (in any form), experiential processes, and age were not found to be significant.

There are several explanations which may account for some of the differences in results. First of all, in signal detection methods, tests perform independently of each other while in logistic regression variables perform in relation to each other. Thus, one variable may account for much of the variance of the entire model. Although this variable would be significant, others which may have been found to be significant had that variable not been included would not be significant in that model. Also, missing data were handled differently in the two analyses. In both cases, only those for whom outcome data were available were included in the analysis. However, in the signal detection methods, those who were missing data for certain variables were excluded only from analyses which included these variables. In the logistic regressions, subjects who were missing data were excluded from the analysis. In Study 1, there were 602 subjects

included in the signal detection analysis and 498 in the logistic regression. In Study 2, the difference was 602 to 509. These differences in the number of subjects entered in each analyses could account for some of the differences in results.

Contributions of Signal Detection to Understand Smoking Cessation. Although signal detection and logistic regression both look at how variables predict a dichotomous outcome, the methods are quite distinct and are able to ascertain quite different information. There are several ways in which signal detection can contribute to logistic regression, which is currently more frequently used. First of all, although logistic regression is a good way of assessing predictors of the outcome variable, signal detection is also able to give the particular cut-off score at which a given predictor best discriminates positive from negative outcome. Also, logistic regression produces an equation using an intercept and weighted scores which is commonly used to predict outcome and plan interventions in research settings. Signal detection produces an algorithm which is easier to interpret. Thus, this end product is more likely to be used to diagnose and treat people in a clinical setting. Signal detection also makes it very easy to understand interaction effects. Subgroups determined by signal detection are based on the interaction of certain variables to produce a certain degree of positive predictive power of the outcome variable. By looking at the algorithm, it is easy to see which variables interact with each other to produce certain levels of positive predictive power.

Ability to Determine Most Efficient Cut-offs

Smoking cessation interventions based on the Transtheoretical model, such as the Expert System interventions, use cut-offs to determine whether an individual receives positive or negative feedback on any given variable. In Study 4, signal detection's ability to determine the most efficient cut-offs for such an intervention was tested. The study was preliminary in that it looked at cut-offs which best discriminated between those who did and did not achieve movement from any pre-action stage to movement into action or maintenance eighteen months later. On the other hand, Expert System intervention cut-offs are set by stage to discriminate those who are likely to achieve any forward stage movement from those who are not. Those who fall above the cut-off on a given variable are given positive feedback, while those who fall below the cut-off are encouraged to make greater use of that particular construct.

The results of Study 4 indicate that signal detection is a potential method for identifying appropriate cut-offs. A strength of using this method is that cut-offs can be mathematically determined to maximize the number of people who get correct feedback and minimize the number of people who get feedback that is not appropriate for them. This is achieved by using signal detection to find the most efficient cut-offs. However, there are also some limitations to this method. In order for signal detection to determine cut-offs, there need to be a large number of subjects in each stage. Also, confirmatory analysis on a second sample would help assess if the cut-offs are reliable.

There were only enough subjects in the contemplation and preparation stages to find cut-offs scores for the predictor variables. The computer program used to run this

analysis (Kraemer, 1992) only gave cut-off scores which were significant predictors at a .1 level. Therefore, cut-offs could not be determined for each variable for those two stages. However, many of the variables for which cut-off scores were determined were consistent with the variables for which feedback is usually given in those stages. For contemplation, cut-offs were determined for pros, cons, temptation, consciousness raising, dramatic relief, and self-reevaluation. In the Expert systems, participants in the contemplation stage receive feedback on these constructs, and also on counterconditioning, environmental reevaluation, helping relationships, stimulus control, and social liberation. For the preparation stage, cut-offs were determined for pros, cons, temptation, consciousness raising, helping relationships, self-liberation, and self-reevaluation. The Expert system also gives feedback on counterconditioning, reinforcement management, stimulus control, and social liberation. A probable explanation for why the variables for which signal detection found cut-offs were not totally consistent with the variables for which Expert Systems give feedback was that there were not enough subjects. This would reduce the power of the study.

Another discrepancy between the results of this study and current Expert System cut-offs was that for consciousness raising (for contemplation and preparation) and social liberation (for preparation), the cut-off score was opposite the direction of feedback. For example, in the Expert System, those who have consciousness raising scores above the cut-off get positive feedback. Yet, the results of this analysis suggest that people who score below 5.42 in contemplation and below 8 in preparation should receive positive feedback. Because such discrepancies can occur, it is important to do confirmatory work

to assess the reliability of the cut-offs and to make sure that the cut-offs are consistent with theory. Since the Transtheoretical model is theory based, and since past research on the model has shown that higher consciousness raising scores in contemplation are predictive of forward stage movement, the results of the signal detection analysis should be questioned in this case. However, this early study shows enough potential in finding cut-offs that may effectively discriminate those who should receive positive or negative feedback to warrant further research.

Limitations of the Current Study

There were several limitations to the current study. One of the key limitations was that, for several reasons, it is questionable whether these results would replicate. For example, for each of the substudies, the actual number of people with positive outcomes compared to the total number of subjects was low (18% of 602 and 11% of 566). A greater number of people with positive outcome relative to total number of subjects may have given more of the variables a chance to discriminate between smokers and non-smokers. However, with such a small overall number of non-smokers, splitting had to be stopped very early for many of the subgroups because there were not enough non-smokers to continue the analysis. Also, with so many subgroups containing a very small number of non-smokers, it may be less likely that the results will replicate.

Another limitation of this study having to do with whether the results would replicate is that the correlations between the predictor variables and outcome were very low. Most all of the correlations were below .2. Since the correlation is an indication of

the overall quality of a variable in predicting the outcome (Kraemer, 1992), this indicates the variables were not very strong predictors. This is another indication that the results may not replicate.

Some of the variables which were found to be significant using the chi-square method, were found to discriminate best at a very extreme level. For example, only 4% of the total sample had stress scores which met the criteria for having a positive test result for perceived stress. The problem with having the cut-off lie at such an extreme is that only a small percentage of people are able to achieve such a score. It should be noted that there were many variables which did not have such extreme cut-offs. The extreme cut-offs may also be a result of having so few people with positive outcomes.

For Study 4, a larger number of subjects is needed to test whether cut-off scores may be determined for variables at all stages. Also, since the ultimate goal would be to determine cut-off scores that predict stage movement rather than smoking cessation, such a study, which was outside of the scope of the present study, should be conducted with a larger sample of smokers.

Another limitation of this study is that, for several reasons, the study design does not really allow for any particular model to be tested. The Transtheoretical model consists of variables which are dynamic in nature. Yet, these variables were only assessed at one time point, so that change in these variables over time was not captured. Also, because the variables are dynamic in nature, they would be expected to predict outcome in a short period of time. Yet, they were assessed six and eighteen months later. Also, the way the variables were tested gave some variables an advantage over others.

Variables which had more splits were allowed to express far more variance than variables which were dichotomized or only split three or four times. For example, the stage of change variable would probably have performed much better if it were entered as a continuous variable. A measure which would have allowed for stage to be measured in this way is the URICA (McConaughy, Prochaska, & Velicer, 1983).

Implications - Signal Detection for the Behavioral Sciences

This study made salient some of the strengths and weaknesses of signal detection methods for the behavioral sciences. Signal detection is a good exploratory method for algorithm development. It is also a good method with which to identify subgroups of individuals who are either more or less likely to succeed at a given outcome.

Interventions could be based around this knowledge. Signal detection also allows one to assess variables as tests for predicting a dichotomous outcome. The variables can be selected based on theory and then assessed empirically with the signal detection methods. Signal detection also makes it easy to see how variables interact with each other. The algorithms make interactions visually easy to understand. Finally, signal detection is a methodological tool for assessing the most sensitive, specific, or efficient cut-offs when a situation calls for this.

However, there are also several shortcomings to signal detection methodology. This is an exploratory technique which requires confirmatory analysis. This method does not give a sense of the power of the results. Thus, it is difficult to get a sense of how

reproducible the results are. Also, the multiple testing and optimizing procedures of signal detection can give a high rate of Type 1 errors (Kraemer, 1992).

Another short coming of signal detection is that at each split, the technique chooses just one predictor variable as the best predictor when it is possible that there are several good predictors. The other good predictors are then excluded from the algorithm because they are not the best predictor. This is a short coming of signal detection because in interventions, it is often useful to have several variables which are highly correlated which are targeted for intervention. This is useful because, although the variables are similar, they tend to capture slightly different aspects of a construct. Thus, it may be easier for people to grasp a concept if it is presented to them in several ways rather than just one. Also, certain individuals may be better able to relate to one aspect of a concept than another. For these reasons, the most parsimonious model is not always the best model for an intervention. Yet, signal detection methods develop the most parsimonious model.

Implications and Future Directions

Smoking Cessation. This study identified subgroups of individuals who were far less likely to quit smoking than the base rate for this study and than several highly successful subgroups. The existence of such subgroups shows the need for the development of interventions which are tailored to particular characteristics of such individuals. The results of this study imply that individually tailored interventions on particular variables may lead to better outcome rates for certain groups than more

generalized interventions. For example, if a subgroup which has a very low smoking cessation rate is characterized by having very low self-efficacy scores and very high pros scores, then interventions prioritized to target change in these variables may have more impact for this subgroup than a more general intervention. Future research is needed to explore this hypothesis.

Another implication of this study is the need for step-care interventions. This study showed that perceived stress was the single variable most likely to discriminate those who are able to quit. Thus, an intervention designed to reduce participants' perceived stress before moving on to intervening on other variables may prove more successful than an intervention targeting change on many variables at once. Again, the step-care approach to interventions should also be designed with subgroup characteristics in mind. The algorithms developed in this study lay out an easy decision chart for the order upon which variables should be intervened. The order in which variables enter the algorithm shows their relative importance, and thus the variables which enter first should be intervened upon first. Future research should examine whether interventions tailored to subgroup characteristics which also intervene in a step-care manner are more effective than currently existing interventions.

This study also found subgroups who had quit rates high above those of the base rate of 18% at eighteen months and 11% at six months. This knowledge can also help behavioral scientists and practitioners develop effective interventions. This can be accomplished by developing interventions where the goal is to help the participants more closely resemble the characteristics of the highly successful groups. Again, a step-care

approach based on the order in which variables entered the algorithm can be useful in such an intervention.

The Transtheoretical Model. This study supported many past findings of how the Transtheoretical model helps to bring about change in a problem behavior such as smoking. Use of behavioral processes was found to be helpful in the short term in this study. Higher self-efficacy was found to be related to smoking cessation. Also, lower importance of the pros were also related to smoking cessation.

Another way in which the Transtheoretical model was supported in this study was that static variables such as demographics were found to be less important in discriminating outcome than dynamic variables which are included in the model. This is especially noteworthy since the Transtheoretical model variables are dynamic over time, these variables may be even better short term than long term predictors of smoking cessation and stage progression. This may be particularly true of this study since many of the subjects underwent interventions which targeted change in these variables. Future research should look at algorithm development for more short term smoking cessation outcome.

The prediction based on the Transtheoretical model which was not supported was that baseline stage of change would enter the algorithms developed in this study. Several hypotheses were proposed to explain why this may have occurred. Future research is still needed to better understand this.

Several enhancements to or new applications of the Transtheoretical model may be proposed as a result of this study. First, it may be fruitful to include some stress

reduction training in Transtheoretical model interventions. Since stress was the first split in all of the algorithms developed, this may suggest that intervening on stress before intervening on variables more directly related to smoking or along with other variables, may help improve the rates of smoking cessation overall.

There are several ways in which inclusion of stress reduction techniques could occur. Level of perceived stress could be measured in the questionnaires, then feedback on this construct could be included as part of the individually tailored computer feedback reports. This could be accomplished in one of two ways. Either the feedback could be included as part of the existing report or participants could get a separate report which would be a Transtheoretical model based stress management intervention. The latter option would require that participants fill out a more extensive questionnaire which would assess stage of change, self-efficacy, decisional balance, and process use for stress management. This would be the most intensive but also most individualized method by which to intervene on perceived stress. A less individualized option would be to provide supplemental materials on stress reduction along with feedback reports. A final option would be to send out the supplemental materials on stress reduction with the first set of reports for those people who fall below the cut-off for having low perceived stress.

Another possible change to the Transtheoretical model based on the findings of this study would be to even further individualize the reports based on subgroup characteristics. A method by which to accomplish this would be to place particular emphasis on the variables which make up an individual's subgroup characteristics. Thus, if a person is in the contemplation stage, he or she would receive feedback on all

variables which are appropriate for this stage, as is currently the case. Further, if this person's subgroup membership indicates that he or she has high self-efficacy, but is not using self-reevaluation much, and has high pros of smoking, this person's report would emphasize these variables by putting them up front or by making the intervention on these variables more intensive than on other variables which may be more important for other subgroups. This could be accomplished in one of several ways. One method would be to individualize the format of the report, so that feedback which is seen as most important for an individual is up front. Another method would be to create another set of paragraph feedback for each variable. If it is a key variable for an individual, then the feedback (positive or negative) may consist of more in depth information. If the variable is not a key variable for this person according to his or her subgroup membership, then less intensive feedback on that construct would be included.

Also, a step-care approach may be used in Transtheoretical model interventions, so that people would receive a series of reports as they currently do, but feedback would be given only on certain variables in each report, not all variables. The reports would be ordered such that people would receive feedback on their most important variables first, then the next most important, and so forth, based on their subgroup characteristics.

Another method by which feedback reports using the Transtheoretical model could be individualized by subgroup would be to take into account the characteristics of the most successful subgroups. The variables which make up these subgroup profiles could be stressed in the reports by making them relatively more intensive than other

variables. Future research is needed to assess whether any of these suggestions would actually enhance the Transtheoretical model or interventions based on this model.

Although several enhancements to the Transtheoretical model are suggested based on the findings of this study, the model itself was not explicitly tested by this study design. Future research using signal detection should explicitly test a model of behavior change. A method for explicitly testing the Transtheoretical model using signal detection would be to look at stage movement by stage over time. For example, the dichotomous outcome for precontemplators would be whether they moved forward from the precontemplation stage or not. Predictor variables should also be assessed in a way that illustrates their dynamic nature. For examples, change in pros from baseline to six months should be assessed instead of simply assessing pros at baseline. It would also be useful to assess change in a shorter period of time, such as one month after assessing the predictor variables, instead of six and eighteen months later. Also, stage of change should be measured using the URICA so that more of the variance of this stage can be captured. In this way, the dynamic nature of the Transtheoretical model would be better tested.

Conclusions. Cigarette smoking is the leading cause of preventable illness and death in the United States. Much research has been conducted to understand the mechanisms that underlie smoking cessation. In this study, variables were chosen according to the leading theory of how people are able to change problem behaviors, the Transtheoretical model. Then statistical decision making was employed to find the most effective combinations of these variables and their cut-off points to predict smoking

cessation. This was the first application of this methodology to the Transtheoretical model. This study supported past research which showed that variables included in the model can help determine who is able to quit smoking. Results of this study suggest that individualized Transtheoretical model based interventions which are also tailored according to subgroup characteristics may help even more people to quit smoking.

TABLES

Table 1: Description of Overall Sample

Characteristics	
N =	602
Age (Mean)	43.5
Sex	
Female	63.5%
Male	36.5%
Ethnicity	
White	98.8%
Black	0.8%
Other	0.4%
Years of Education (Average)	14.2
Marital Status	
Single	12.8%
Married	67.6%
Living Together	2.5%
Divorced	11.5%
Separated	2.3%
Widowed	3.3%
Gross Yearly Income	
Under 5,000 per year	8.4%
5,000 - 14,999 per year	20.6%
15,000 - 24,999 per year	31.1%
25,000 - 34,999 per year	16.4%
35,000 - 44,999 per year	6.1%
45,000 - 54,999 per year	2.4%
55,000 - 64,999 per year	1.5%
Over 65,000 per year	1.9%

Table 2: Conditional Probabilities of Signal Detection

Diagnosis	Test	
	Smoker	Non-Smoker
smoker	“Hit” or “True Positive” $P(S s) = (\text{sum of responses} > \text{cutoff} / \text{sum of responses})$	“Miss” or “False Negative” $P(NS s) = (\text{sum of responses} \leq \text{cutoff} / \text{sum of responses})$
non-smoker	“False Alarm” or “False Positive” $P(S ns) = (\text{sum of responses} \leq \text{cutoff} / \text{sum of responses})$	“Correct Rejection” or “True Negative” $P(NS ns) = (\text{sum of responses} > \text{cutoff} / \text{sum of responses})$

Table 3: Predictors Included in Study 1**Correlation with Outcome and Range of Possible Splits**

Variable	Corr	Range
Intervention 1	-.107	0-1
Intervention 2	.006	0-1
Intervention 3	.104	0-1
Intervention 4	-.001	0-1
Precontemplation	-.084	0-1
Contemplation	-.049	0-1
Preparation	.113	0-1
Sex	.052	0-1
Age	.099	17-74
Education	.062	9-21
Addiction	-.067	0-10
Perceived Stress	.075	5-20
Cons	.091	10-50
Pros	-.096	10-50
Income	-.034	0-1
Counter	.014	4-20
Conditioning		
Consciousness	-.010	4-20
Raising		
Dramatic Relief	.076	4-20
Environmental	.006	4-20
Reevaluation		
Helping	.003	4-20
Relationships		
Reinforcement	.059	4-20
Management		
Stimulus Control	.005	4-20
Self-Liberation	.078	4-20
Social Liberation	-.004	4-20
Self-Reevaluation	.104	4-20
Confidence	.101	20-100
Temptation	-.107	20-100

Table 4: Direct Logistic Regression for Study 1

Direct Logistic Regression Analysis on Smoking Cessation versus Continued Smoking with 25 Predictors

Variable	Parameter Estimate	S.E.	Wald χ^2	Odds Ratio
Intervention 1	-0.4026	0.3842	1.0981	0.669
Intervention 2	0.2092	0.3353	0.3893	1.233
Intervention 3	0.5595	0.3384	2.7341*	1.750
Precontemplation	-0.7.83	0.5170	1.8769*	0.492
Contemplation	-0.3625	0.2817	1.6565*	0.696
Sex	0.7913	0.3156	6.6919***	2.206
Age	0.0256	0.0106	5.8191**	1.026
Education	0.0232	0.0499	0.2156	1.023
Addiction	-0.0121	0.0767	0.0249	0.988
Stress	0.0770	0.0429	3.2270*	1.080
Cons	0.00902	0.0219	0.1699	1.009
Pros	-0.0138	0.0187	0.5404	0.986
Income	-0.2952	0.2789	1.1203	0.744
CC	-0.0394	0.0536	0.5403	0.961
CR	-0.0828	0.0451	3.3738*	0.921
DR	0.0231	0.0380	0.5442	1.023
ER	-0.0308	0.0378	0.6621	0.970
HR	-0.00578	0.0392	0.0218	0.994
RM	0.0512	0.0419	1.4917	1.053
SC	-0.0508	0.0540	0.8862	0.950
SL	0.0235	0.0390	0.3623	1.024
SO	-0.0449	0.0543	0.6857	0.956
SR	0.0776	0.0496	2.4531*	1.081
Confidence	-0.00712	0.0127	0.3146	0.993
Temptation	-0.0247	0.0111	4.9546*	0.976

*p < .2 **p < .05 ***p < .01

Table 5: Predictors Included In Study 2
Correlation with Outcome and Range of Possible Splits

Variable	Corr	Range
Intervention	.081719	1-4
Stage	.126722	1-3
Sex	.052261	0-1
Age	.099170	17-74
Education	.062315	9-21
Addiction	-.067503	0-10
Income	-.034852	0-1
Ethnicity	-.069936	0-1
Confidence - Negative Affect	.086729	4-20
Confidence - Positive Social	.078160	4-20
Confidence - Craving	.091834	4-20
Experiential Processes	.049598	20-100
Behavioral Processes	.059243	20-100
Perceived Stress	.075089	5-20
Cons	.091117	10-50
Pros	-.096978	10-50

Table 6: Logistic Regression for Study 2

Direct Logistic Regression Analysis on Smoking Cessation versus Continued Smoking with 16 Predictors

Variable	Parameter Estimate	S.E.	Wald χ^2	Odds Ratio
Intervention	0.1437	0.1075	1.7874*	1.155
Stage	0.3657	0.2115	2.9894*	1.441
Sex	0.6543	0.2960	4.8845**	1.924
Age	0.0246	0.0102	5.8435**	1.025
Ethnicity	-1.5687	0.8871	3.1271*	0.208
Education	0.0435	0.0482	0.8150	1.044
Addiction	-0.00890	0.0749	0.0141	0.991
Stress	0.0615	0.0412	2.2348*	1.063
Cons	0.0293	0.0204	2.0520*	1.030
Pros	-0.0278	0.0182	2.3381*	0.973
Income	-0.1924	0.2632	0.5345	0.825
Behavioral Procs	-0.00262	0.0155	0.0286	0.997
Experiential Procs	-0.0108	0.0131	0.6850	0.989
Conf. - Pos. Soc	-0.0204	0.0351	0.3382	0.980
Conf. - Neg. Affect	0.0200	0.0338	0.3482	1.020
Conf. - Habit	0.0222	0.0377	0.3465	1.022

*p < .2 **p < .05

Table 7: Predictors Included in Study 3
Correlation with Outcome and Range of Possible Splits

Variable	Corr	Range
Intervention	.115686	1-4
Stage	.073994	1-3
Sex	.014227	0-1
Age	.029644	17-74
Education	.068611	9-21
Addiction	-.118438	0-10
Income	.013077	0-1
Ethnicity	-.012991	0-1
Confidence - Negative Affect	.060072	4-20
Confidence - Positive Social	-.006180	4-20
Confidence - Craving	.056564	4-20
Experiential Processes	-.038641	20-100
Behavioral Processes	.058310	20-100
Perceived Stress	.105425	5-20
Cons	-.003923	10-50
Pros	-.026316	10-50

Table 8: Precontemplation - Most Efficient Cut-offs

Test	Correlation with Outcome	N
Pros	-.094069	73
Cons	.019660	72
Confidence	.068738	73
Temptation	-.072175	70
CC	.040626	73
CR	-.070184	73
DR	-.146552	72
ER	-.044800	72
HR	.027390	73
RM	-.037448	73
SC	.058630	72
SL	.063676	73
SO	.073734	73
SR	.196146	72

Table 9: Contemplation - Most Efficient Cut-offs

Test	Cut-off	Chi-square	P-value	Correlation with Outcome	N
Pros	≤ 22	4.14	$< .05$	-.020966	335
Cons	≥ 48	8.91	$< .01$.114019	335
Confidence	≥ 54	5.06	$< .05$.071368	328
Temptation	≤ 69	3.40	$< .1$	-.059245	329
CC				-.003289	332
CR	≤ 8	2.71	$< .1$	-.019053	341
DR	≥ 18	4.87	$< .05$.106126	332
ER				.003412	332
HR				-.005834	341
RM	≥ 11	2.24	$< .1$.065129	341
SC				-.004089	332
SL				.024591	341
SO				.007158	341
SR	≥ 18	7.10	$< .01$.118570	331

Table 10: Preparation - Most Efficient Cut-offs

Test	Cut-off	Chi-square	P-value	Correlation with Outcome	N
Pros	≤ 19	7.83	$< .01$	-.164987	183
Cons	≥ 44	1.02	$< .1$	-.012621	185
Confidence	≥ 59	7.19	$< .01$.062393	182
Temptation	≤ 66	6.26	$< .05$	-.141121	177
CC				-.036115	181
CR	≤ 8	5.42	$< .05$	-.063866	185
DR	≥ 20	2.01	$< .1$	-.042664	181
ER				-.037900	181
HR	≥ 11	5.69	$< .05$	-.002100	185
RM				-.008194	185
SC				-.069063	179
SL	≥ 17	3.23	$< .1$.030470	185
SO	≤ 13	3.28	$< .1$	-.048173	185
SR					

FIGURES

Figure 1: Sample ROC Curve

Sample ROC Curve

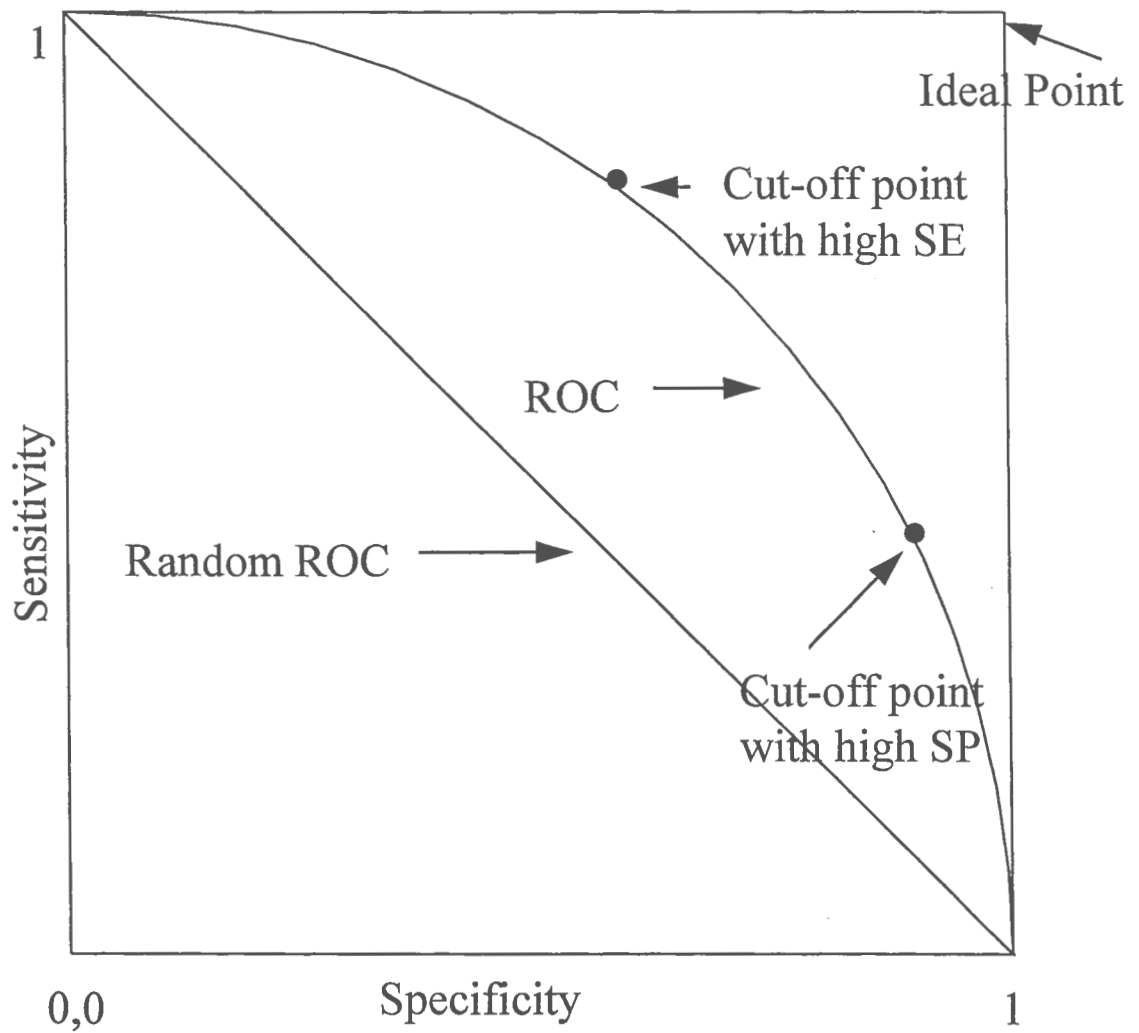
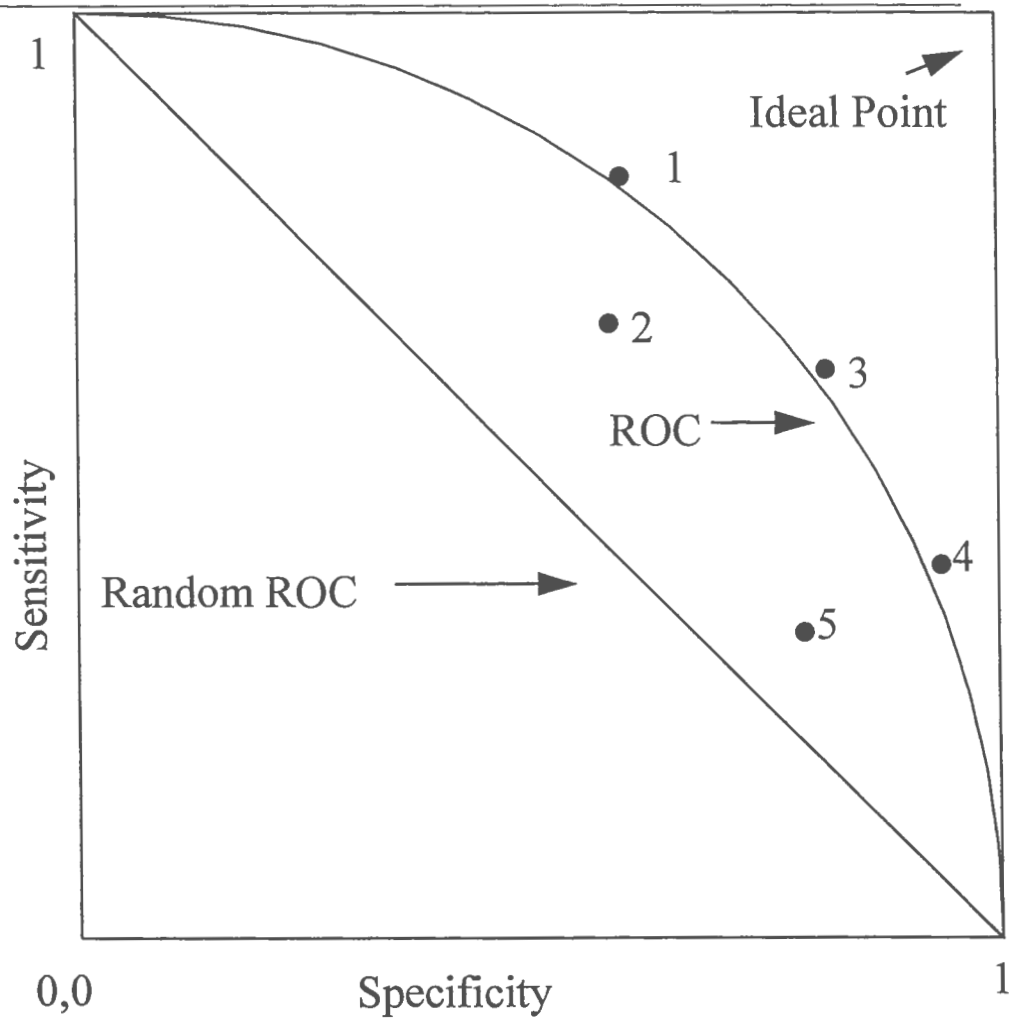


Figure 2: Sample Test Family ROC

Sample Test Family ROC



1 = Most Sensitive Point

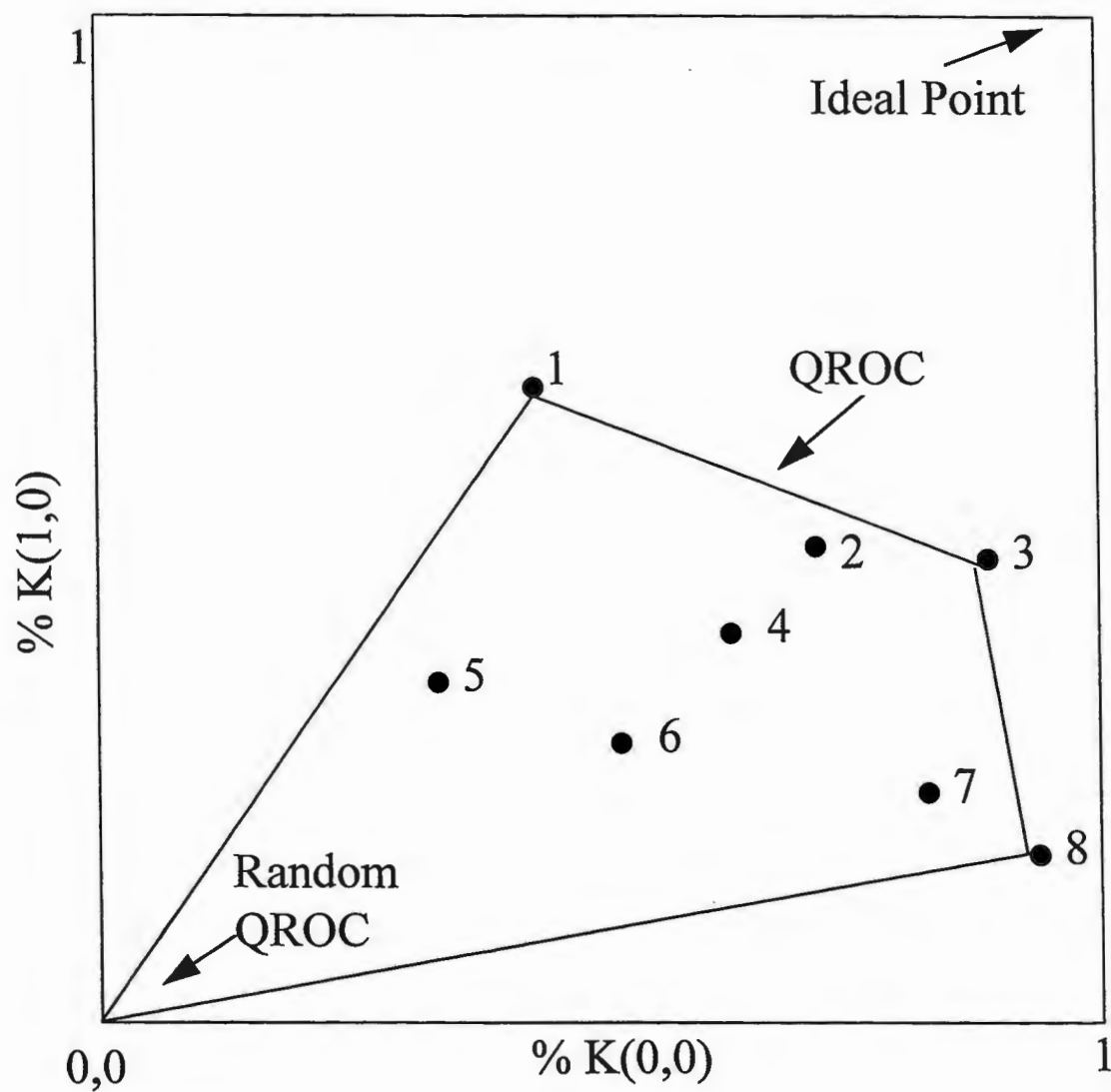
4 = Most Specific Point

3 = Most Efficient Point

2 and 5 = Tests which are not as good predictors as tests on the ROC curve

Figure 3: Sample QROC

Sample QROC Curve



1 = most sensitive test with highest quality

8 = most specific test with highest quality

3 = most efficient test with highest quality

2,4,5,6, and 7 = not the best quality test in this example

Figure 4: Study 1: Initial Algorithm (1)

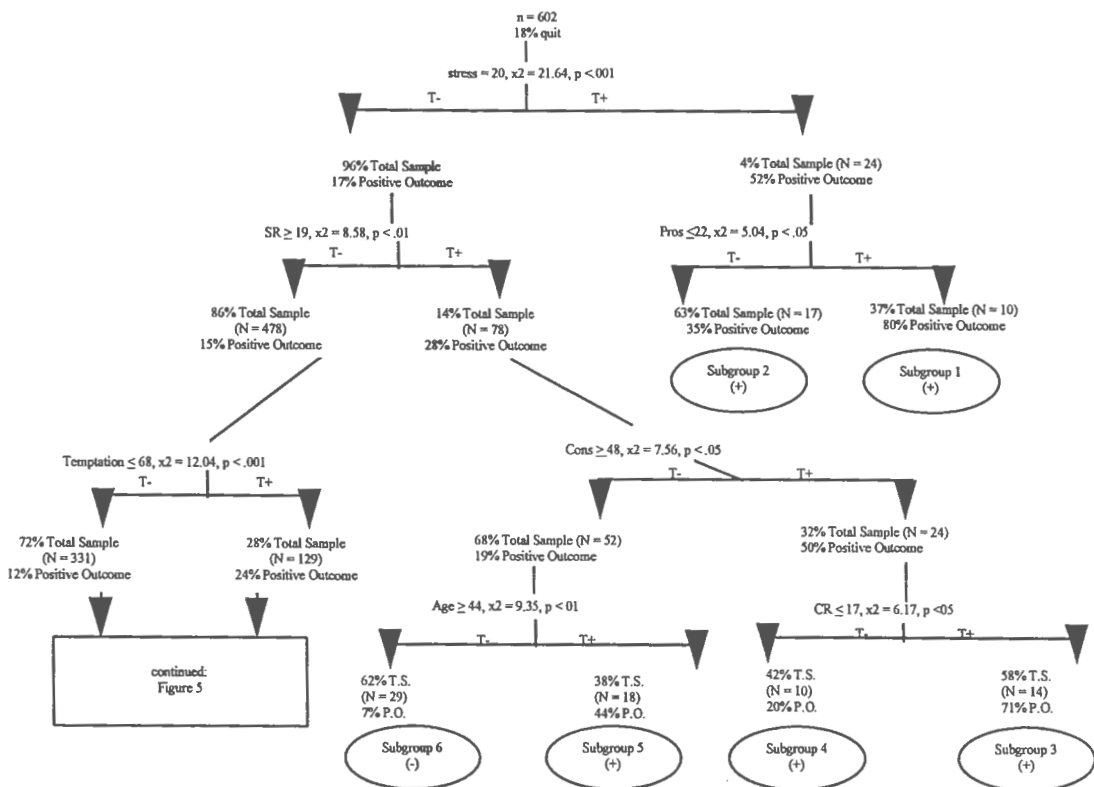


Figure 5: Study 1: Initial Algorithm (2)

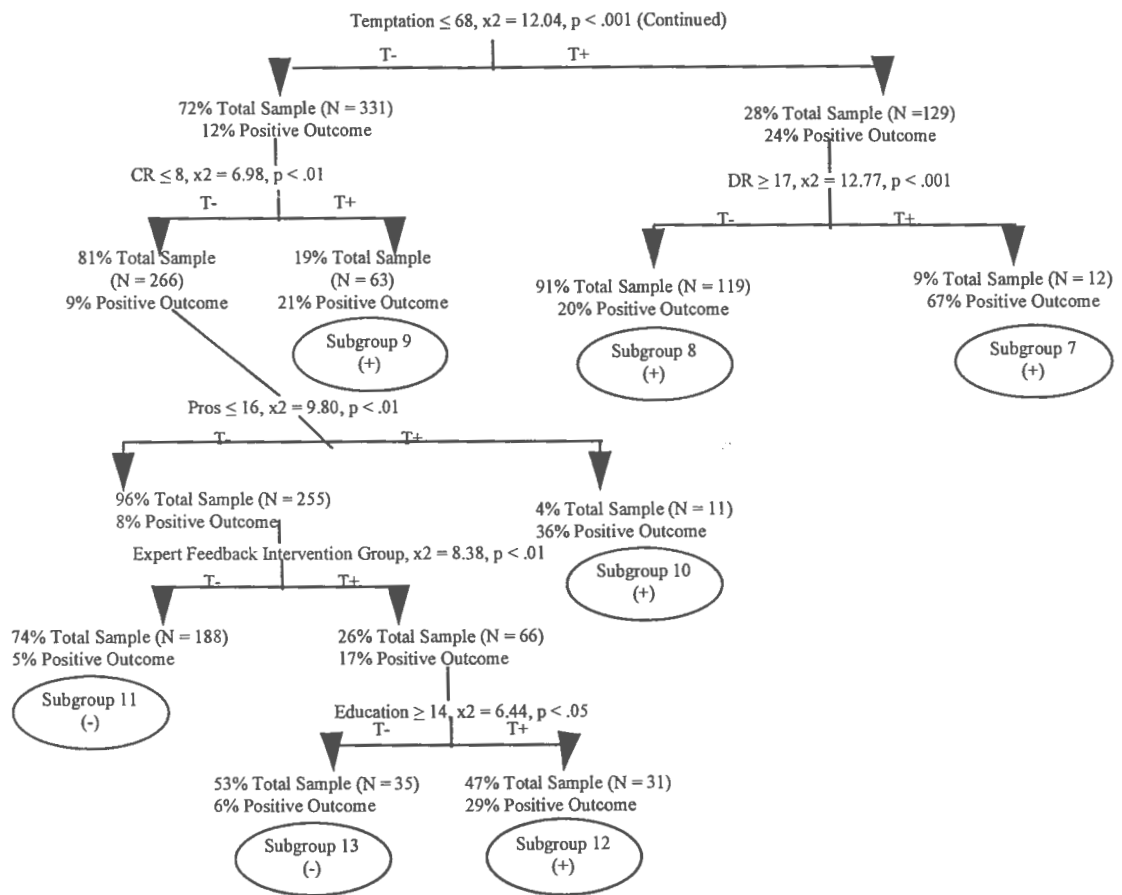
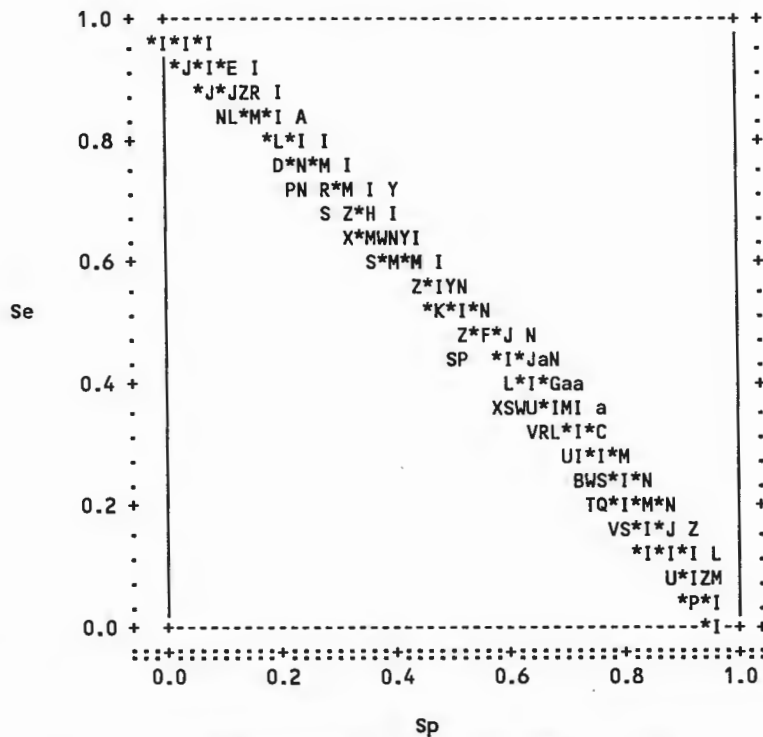


Figure 6: Study 1: ROC Graph for All Tests

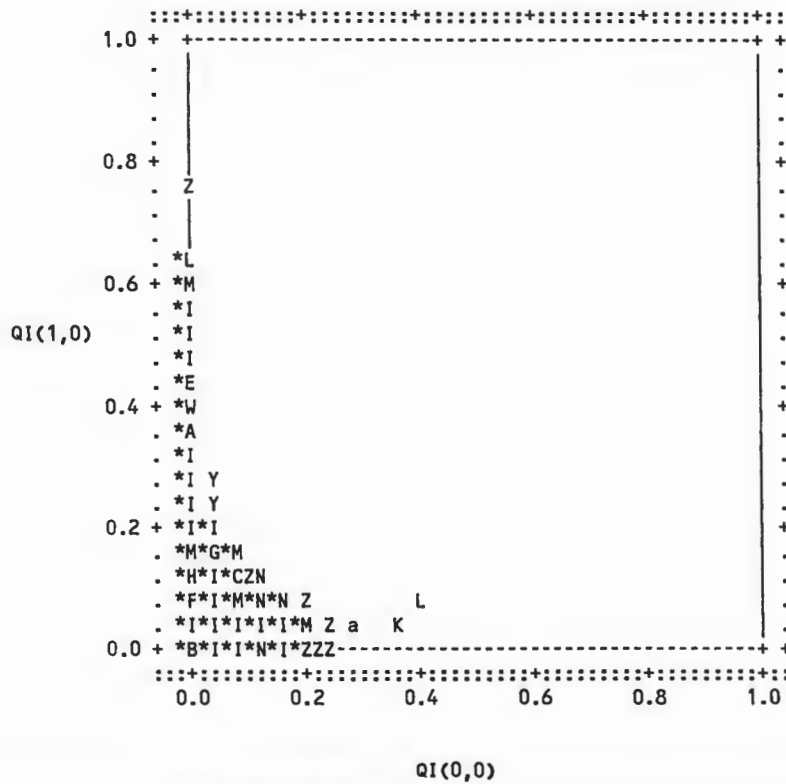
Study 1: ROC Graph Demonstrating All Tests



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 7: Study 1: QROC Graph for All Tests

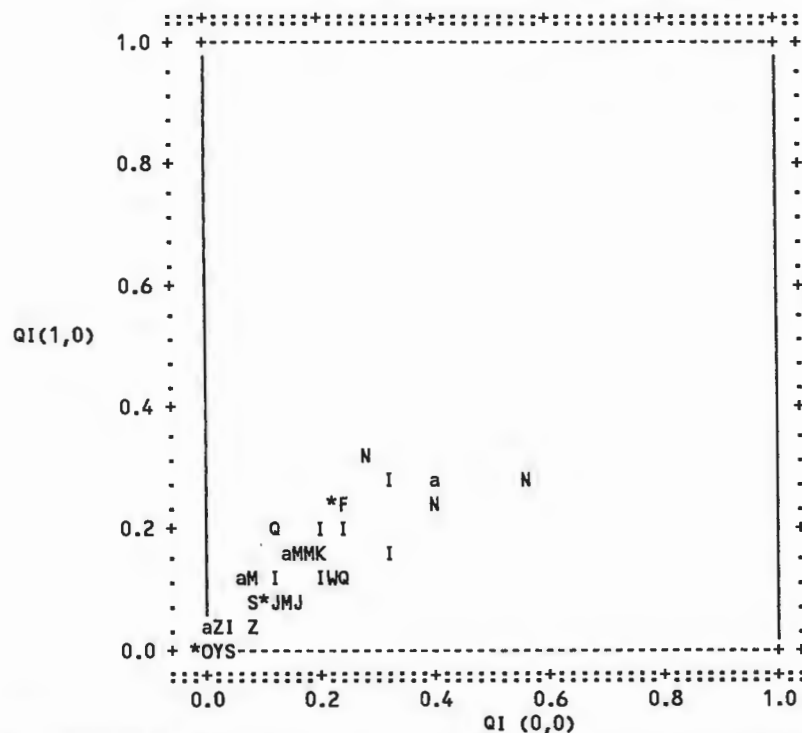
Study 1: QROC Graph Demonstrating All Tests



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 8: Study 1: QROC - Perceived Stress ≥ 20

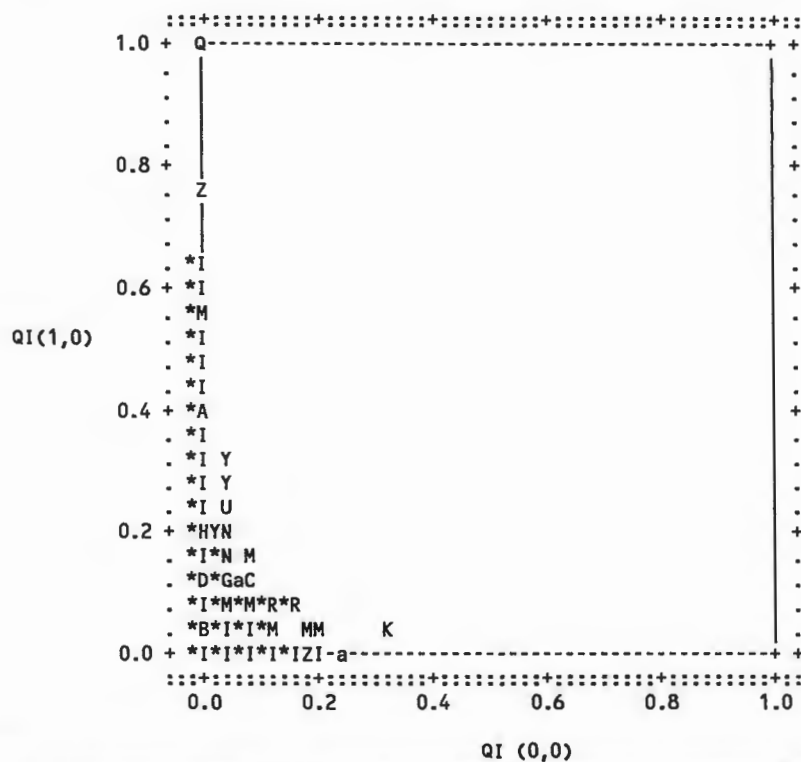
Study 1: QROC Graph Demonstrating Perceived Stress ≥ 20



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 9: Study 1: QROC - Perceived Stress < 20

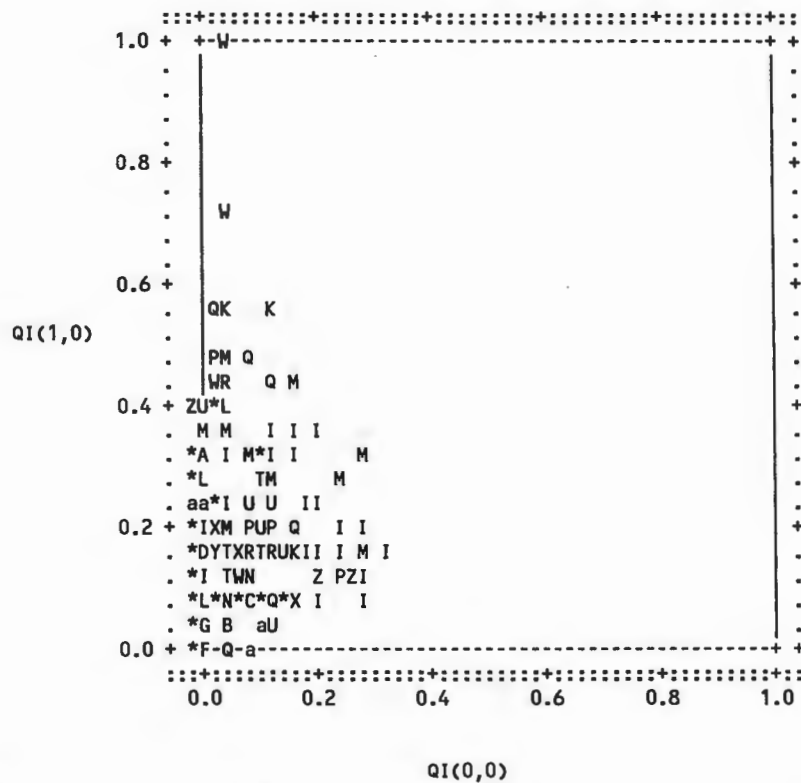
Study 1: QROC Graph Demonstrating Perceived Stress < 20



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 10: Study 1: QROC - SR ≥ 19

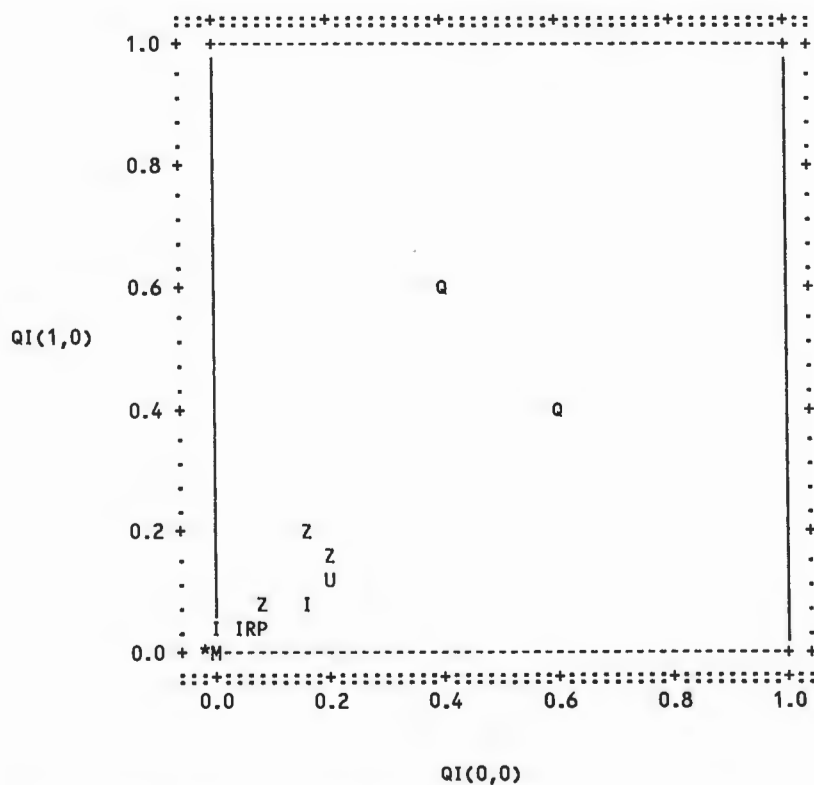
Study 1: QROC Graph Demonstrating Perceived Stress < 20 and SR ≥ 19



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 11: Study 1: QROC - Cons ≥ 48

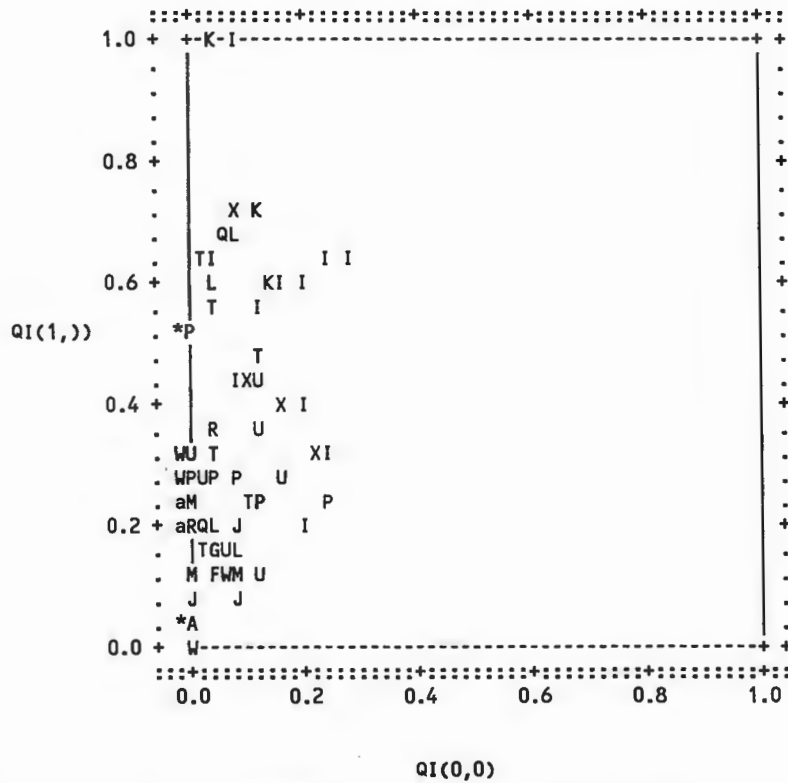
Study 1: QROC Graph Demonstrating Perceived Stress < 20 and SR ≥ 19 and cons ≥ 48



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 12: Study 1: QROC - Cons < 48

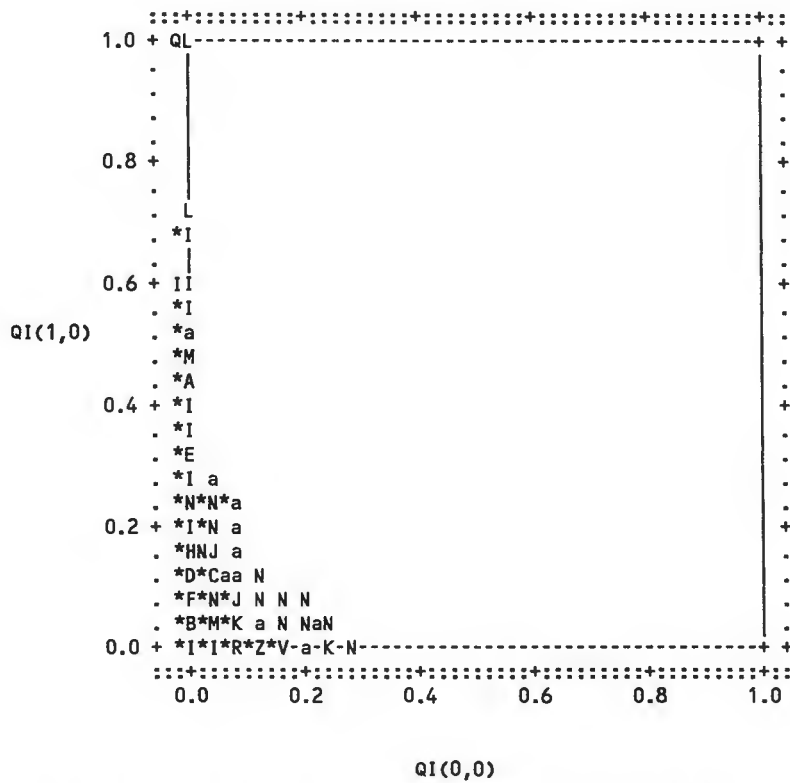
Study 1: QROC Graph Demonstrating Perceived Stress < 20 and SR ≥ 19 and cons < 48



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 13: Study 1: QROC - SR < 19

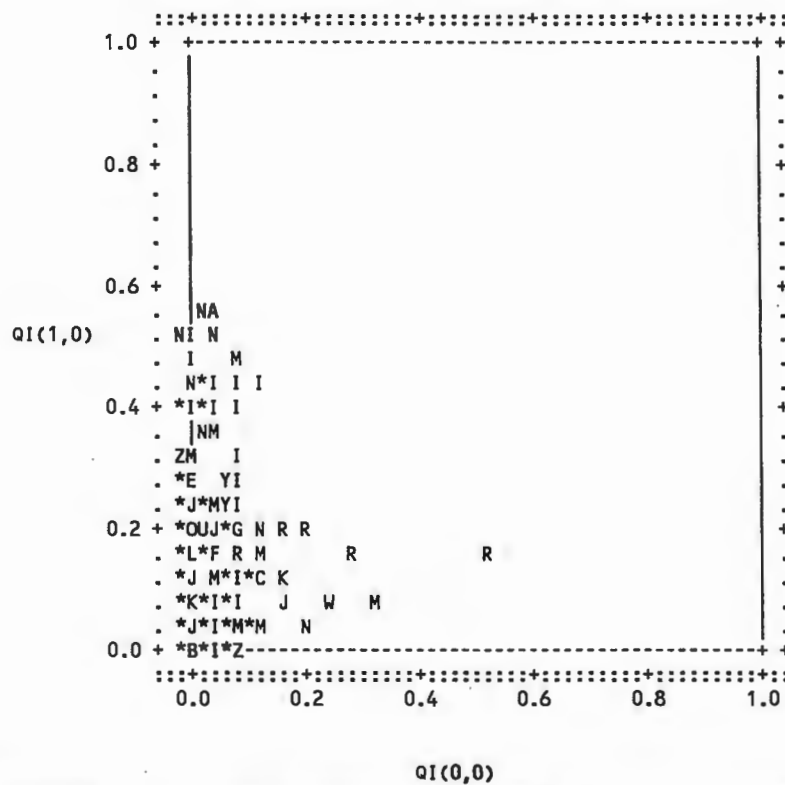
Study 1: QROC Graph Demonstrating Perceived Stress < 20 and SR < 19



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 14: Study 1: QROC - Temptations ≤ 68

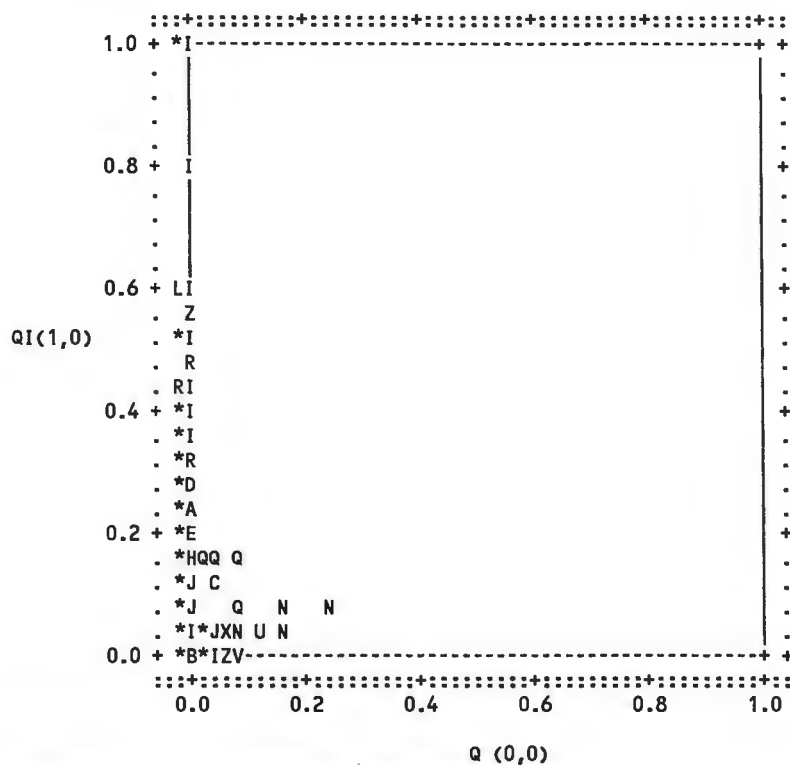
Study 1: QROC Graph Demonstrating Perceived Stress < 20 and SR < 19 and Temptation ≤ 68



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 15: Study 1: QROC Temptation > 68

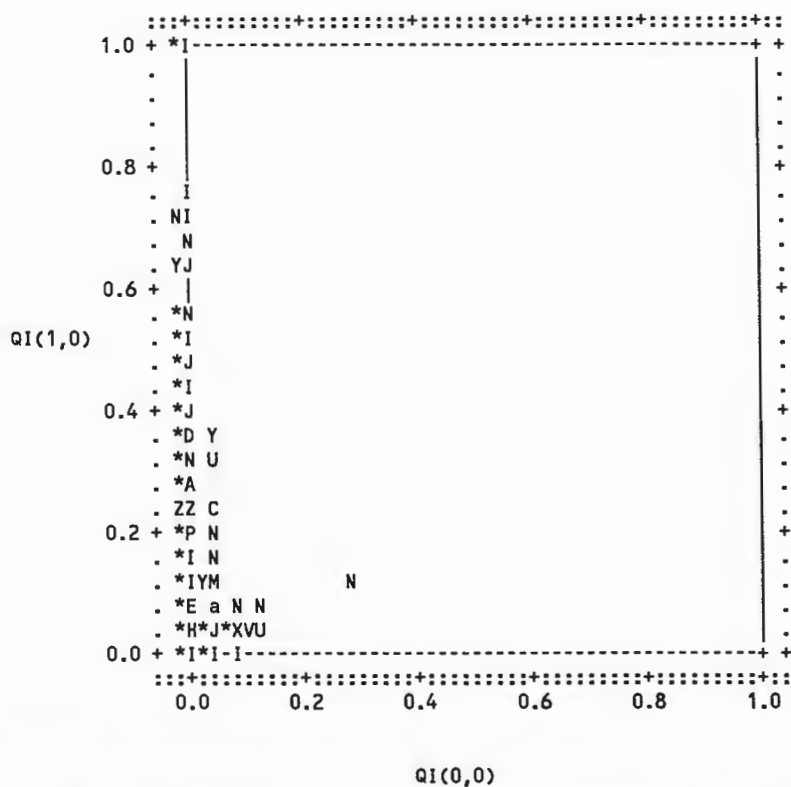
Study 1: QROC Graph Demonstrating Perceived Stress < 20 and SR < 19 and Temptation > 68



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 16: Study 1: QROC - CR > 8

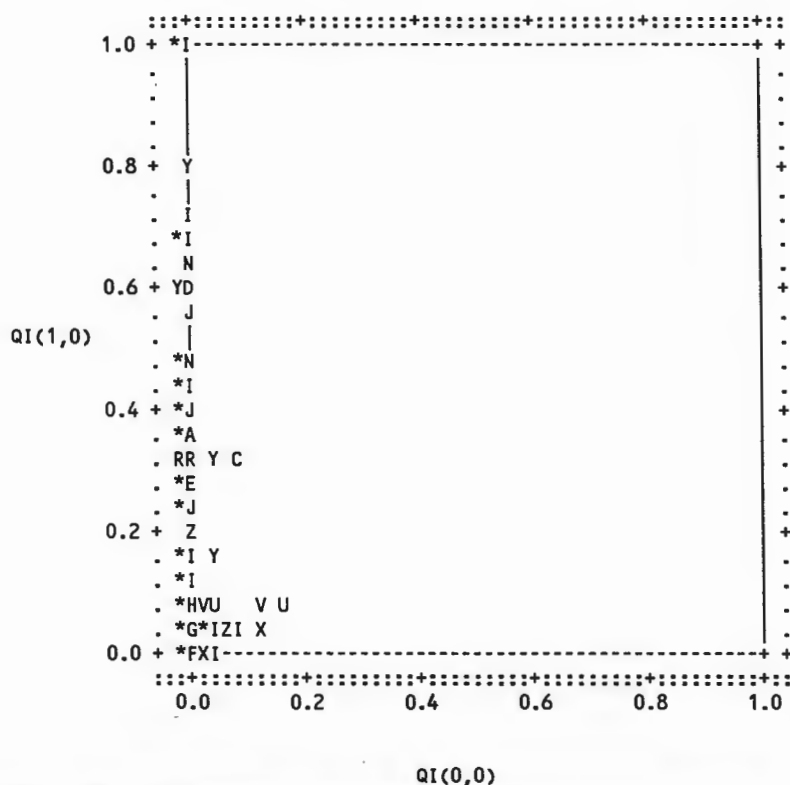
Study 1: QROC Graph Demonstrating Perceived Stress < 20 and SR < 19 and Temptation > 68 and CR > 8



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 17: Study 1: QROC - Pros > 16

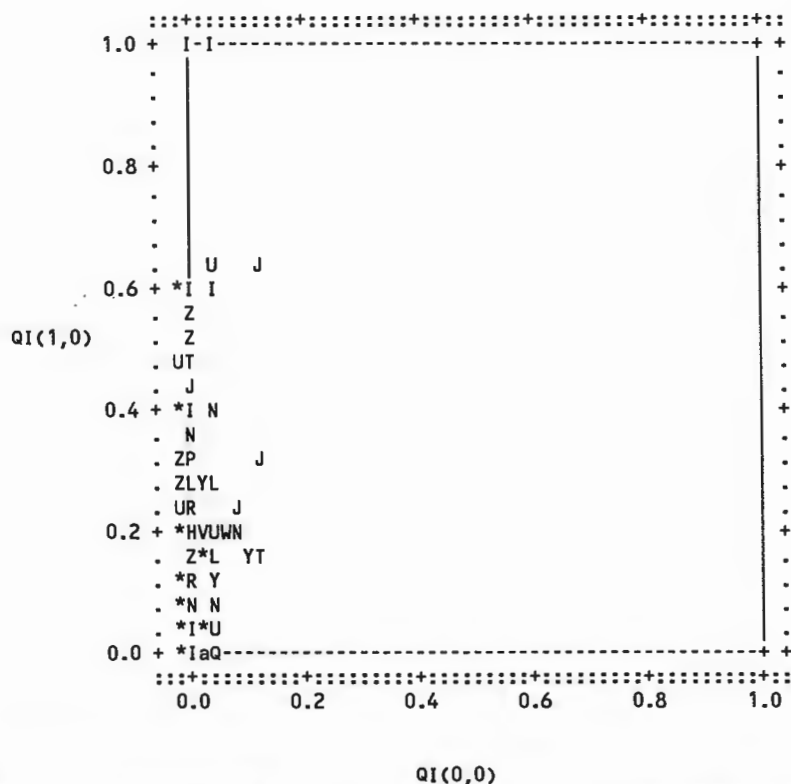
Study 1: QROC Graph Demonstrating Perceived Stress < 20 and SR < 19 and Temptation > 68 and CR > 8 and Pros > 16



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 18: Study 1: QROC: Intervention = 3

Study 1: QROC Graph Demonstrating Perceived Stress < 20 and SR < 19 and Temptation > 68 and CR > 8 and Pros ≥ 17 and Intervention = 3



Variable	Symbol	Variable	Symbol
Intervention 1	A	Income	O
Intervention 2	B	Counter Conditioning	P
Intervention 3	C	Consciousness Raising	Q
Intervention 4	D	Dramatic Relief	R
Precontemplation	E	Environmental Reevaluation	S
Contemplation	F	Helping Relationships	T
Preparation	G	Reinforcement Management	U
Sex	H	Stimulus Control	V
Age	I	Self-liberation	W
Education	J	Social Liberation	X
Addiction	K	Self-Reevaluation	Y
Perceived Stress	L	Confidence	Z
Cons	M	Temptation	a
Pros	N	Multiple Tests	*

Figure 19: Study 1: Final Algorithm (1)

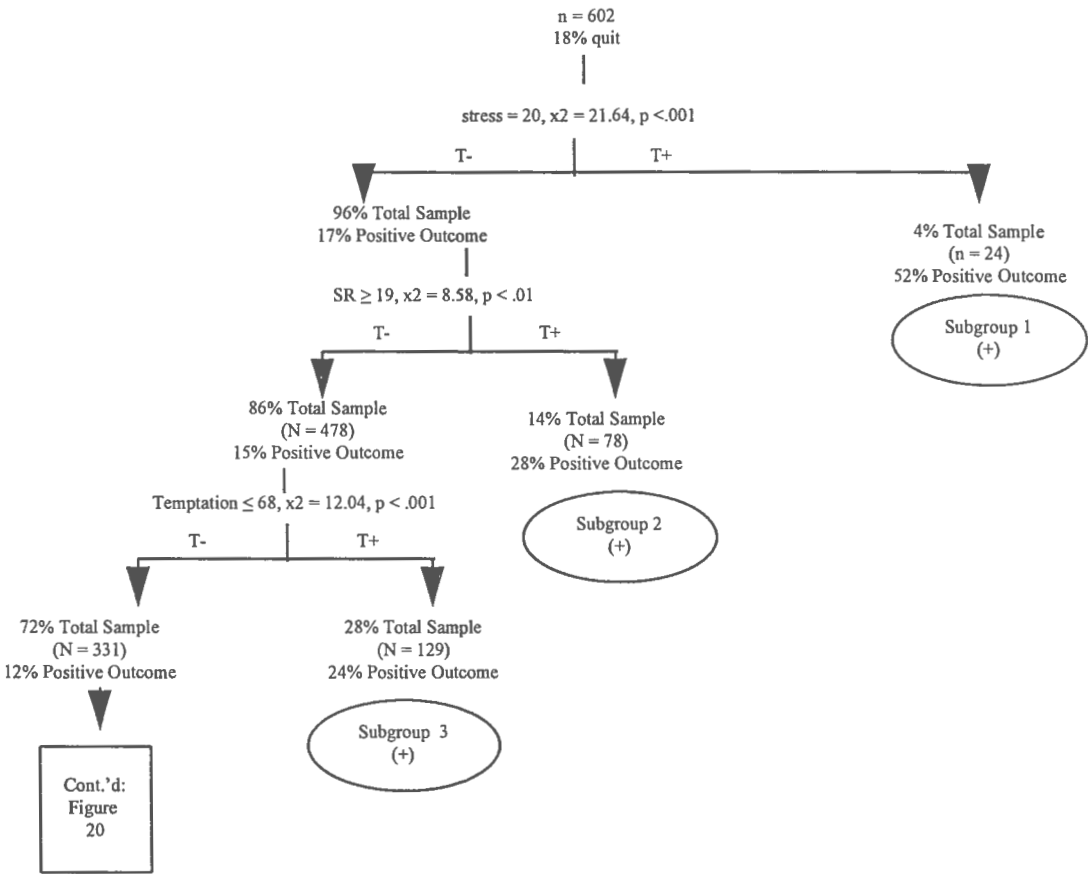


Figure 20: Study 1: Final Algorithm (2)

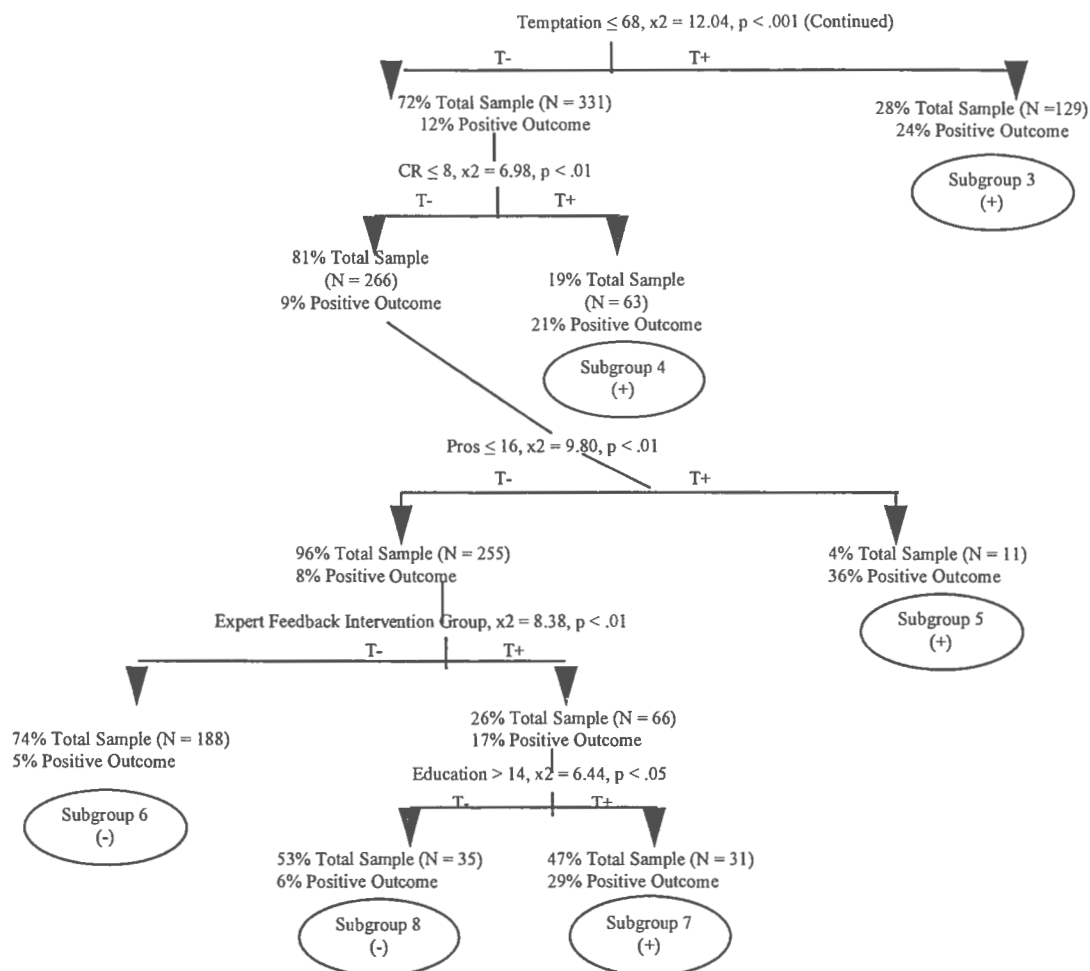


Figure 21: Study 2: Initial Algorithm (1)

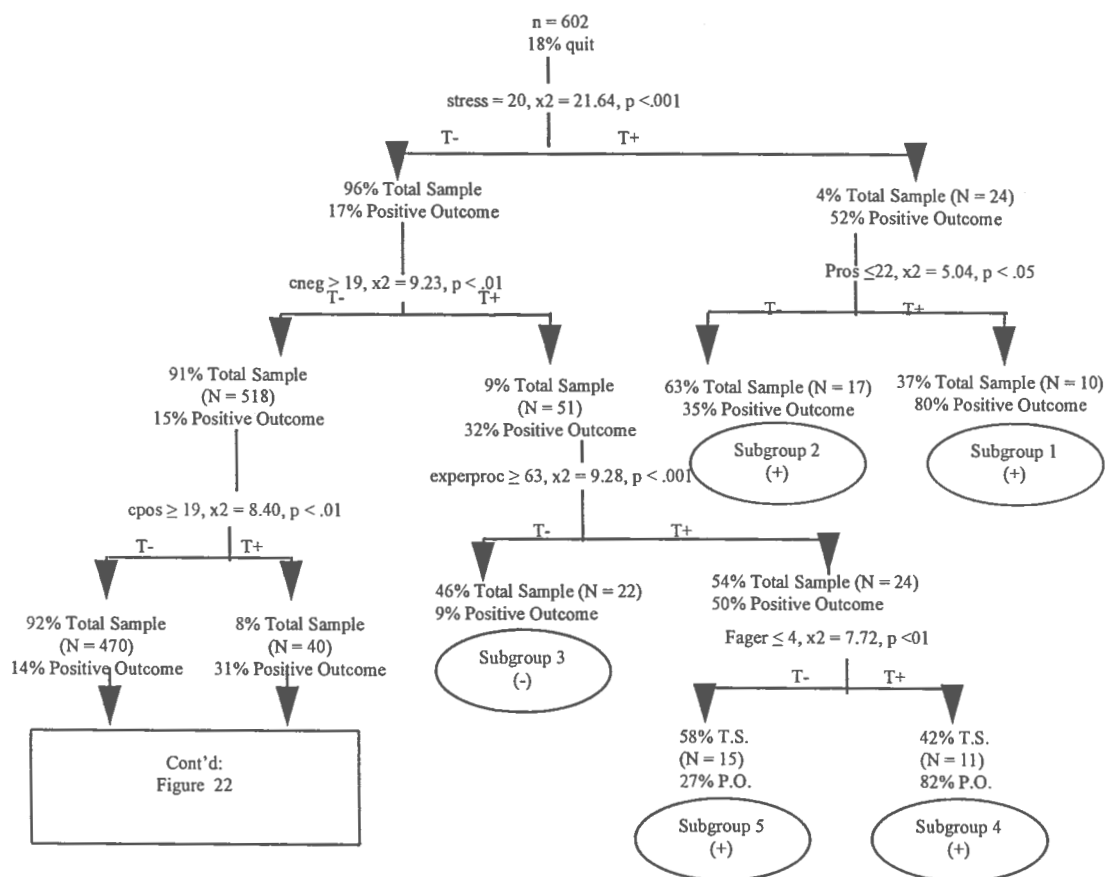
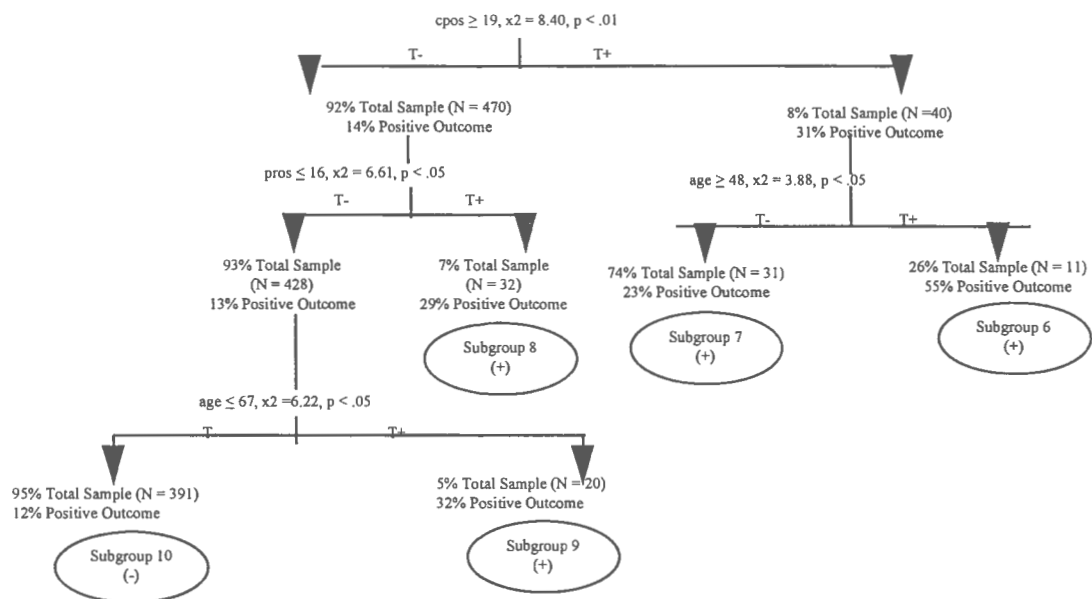


Figure 22: Study 2: Initial Algorithm (2)



Study 2: QROC Graph Demonstrating All Tests

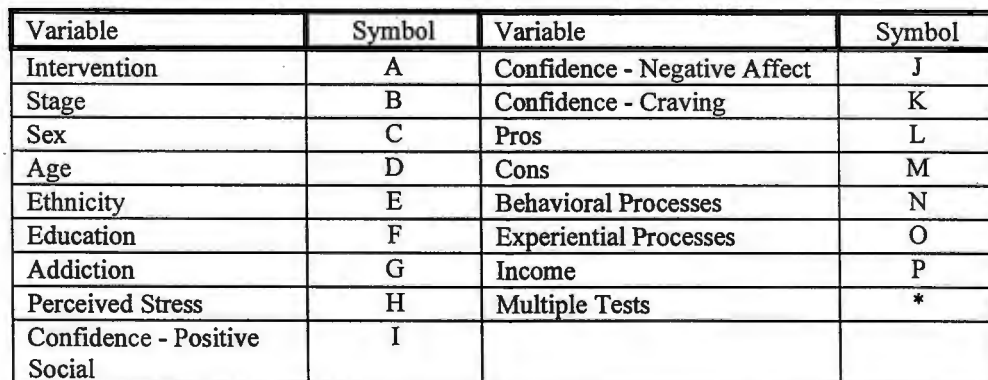
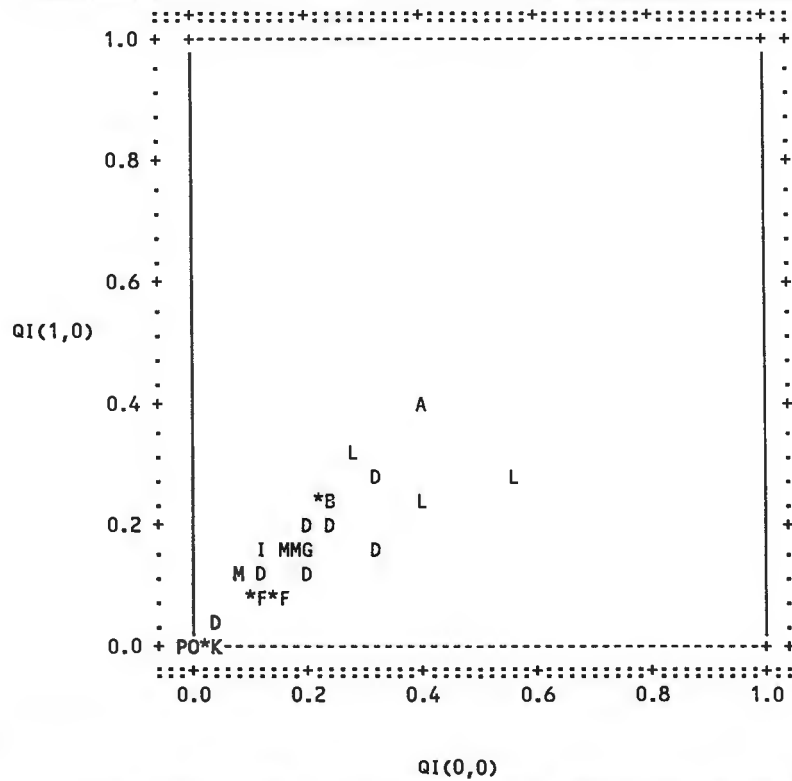


Figure 24: Study 2: Perceived Stress ≥ 20

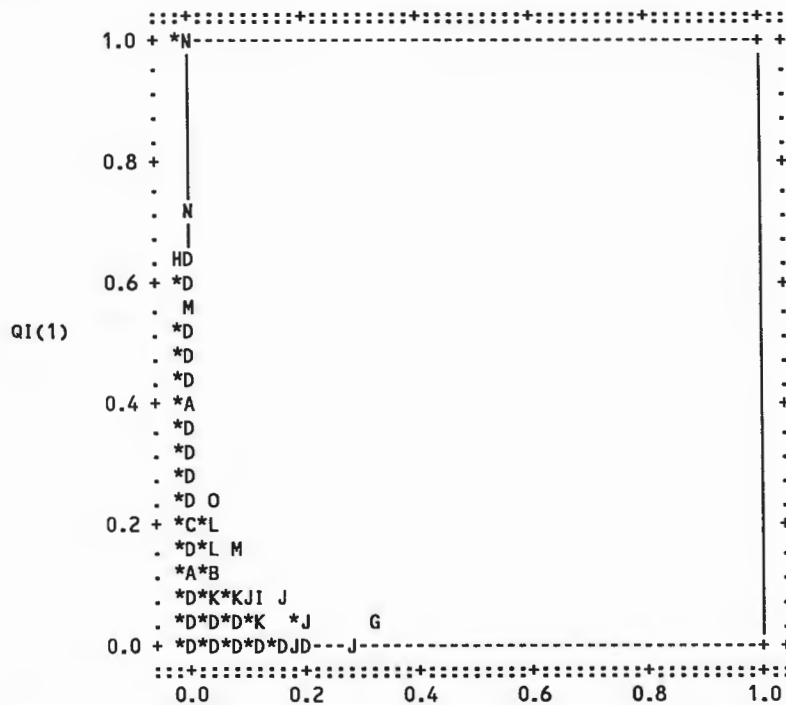
Study 2: QROC Graph Demonstrating Perceived Stress ≥ 20



Variable	Symbol	Variable	Symbol
Intervention	A	Confidence - Negative Affect	J
Stage	B	Confidence - Craving	K
Sex	C	Pros	L
Age	D	Cons	M
Ethnicity	E	Behavioral Processes	N
Education	F	Experiential Processes	O
Addiction	G	Income	P
Perceived Stress	H	Multiple Tests	*
Confidence - Positive Social	I		

Figure 25: Study 2: Perceived Stress < 20

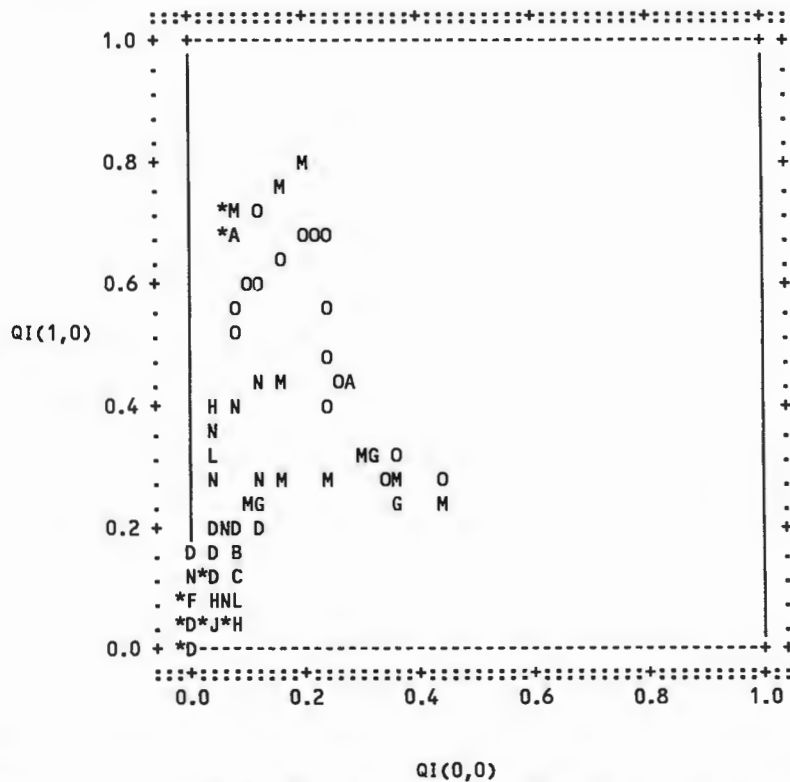
Study 2: QROC Graph Demonstrating Perceived Stress < 20



QI(0)			
Variable	Symbol	Variable	Symbol
Intervention	A	Confidence - Negative Affect	J
Stage	B	Confidence - Craving	K
Sex	C	Pros	L
Age	D	Cons	M
Ethnicity	E	Behavioral Processes	N
Education	F	Experiential Processes	O
Addiction	G	Income	P
Perceived Stress	H	Multiple Tests	*
Confidence - Positive Social	I		

Figure 26: Study 2: Conf Neg ≥ 19

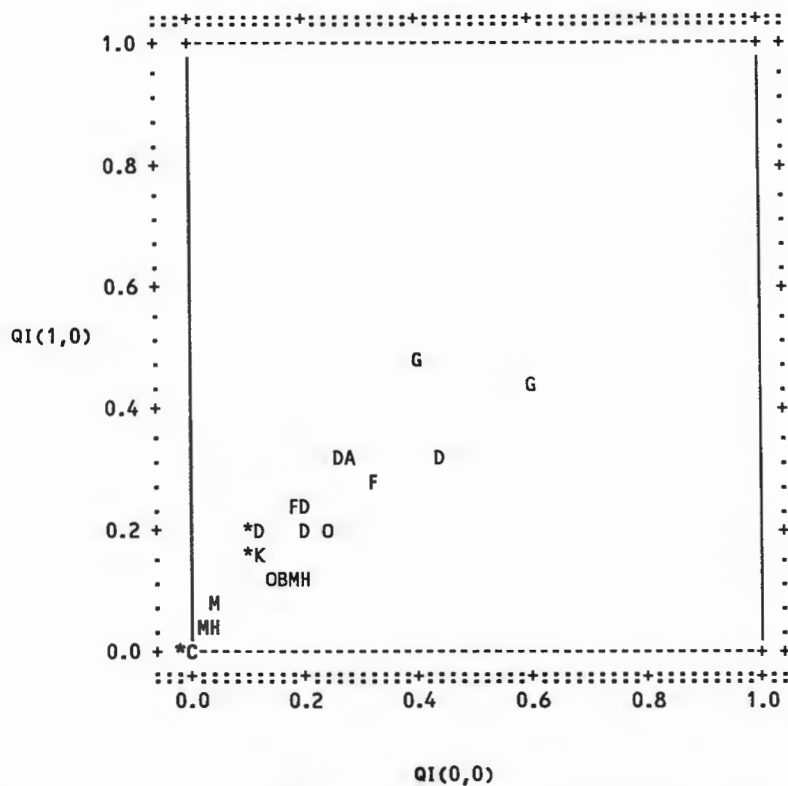
Study 2: QROC Graph Demonstrating Perceived Stress < 20 and Confidence (Negative Affect) ≥ 19



Variable	Symbol	Variable	Symbol
Intervention	A	Confidence - Negative Affect	J
Stage	B	Confidence - Craving	K
Sex	C	Pros	L
Age	D	Cons	M
Ethnicity	E	Behavioral Processes	N
Education	F	Experiential Processes	O
Addiction	G	Income	P
Perceived Stress	H	Multiple Tests	*
Confidence - Positive Social	I		

Figure 27: Study 2: Experiential Processes ≥ 63

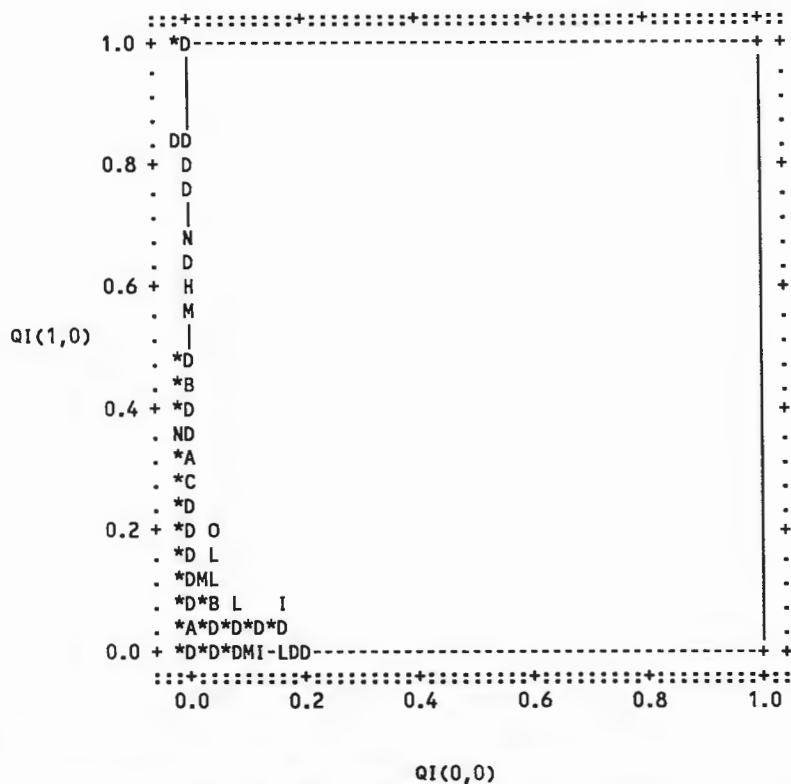
Study 2: QROC Graph Demonstrating Perceived Stress < 20 and Confidence (Negative Affect) ≥ 19 and Experiential Processes ≥ 63



Variable	Symbol	Variable	Symbol
Intervention	A	Confidence - Negative Affect	J
Stage	B	Confidence - Craving	K
Sex	C	Pros	L
Age	D	Cons	M
Ethnicity	E	Behavioral Processes	N
Education	F	Experiential Processes	O
Addiction	G	Income	P
Perceived Stress	H	Multiple Tests	*
Confidence - Positive Social	I		

Figure 28: Study 2: Conf Neg < 19

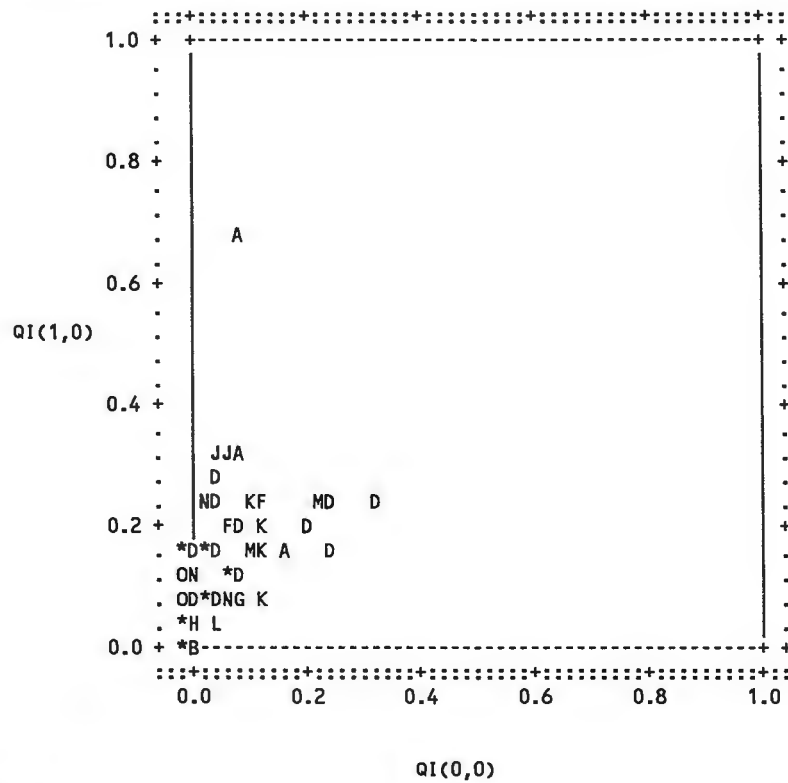
Study 2: QROC Graph Demonstrating Perceived Stress < 20 and Confidence (Negative Affect) < 19



Variable	Symbol	Variable	Symbol
Intervention	A	Confidence - Negative Affect	J
Stage	B	Confidence - Craving	K
Sex	C	Pros	L
Age	D	Cons	M
Ethnicity	E	Behavioral Processes	N
Education	F	Experiential Processes	O
Addiction	G	Income	P
Perceived Stress	H	Multiple Tests	*
Confidence - Positive Social	I		

Figure 29: Study 2: Conf Pos ≥ 19

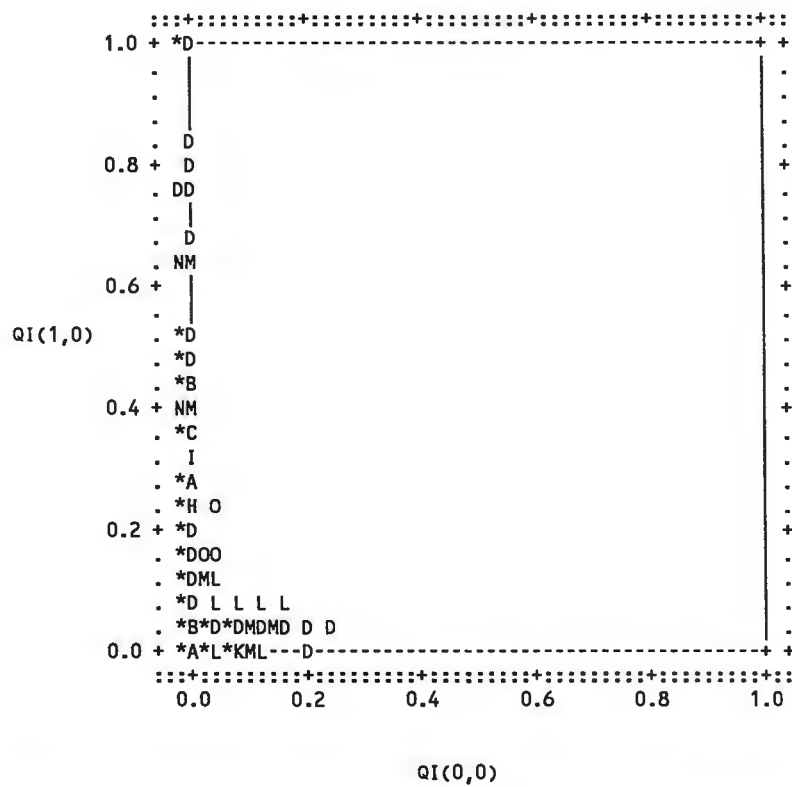
Study 2: QROC Graph Demonstrating Perceived Stress < 20 and Confidence (Negative Affect) < 19 and Confidence (Positive Social) ≥ 19



Variable	Symbol	Variable	Symbol
Intervention	A	Confidence - Negative Affect	J
Stage	B	Confidence - Craving	K
Sex	C	Pros	L
Age	D	Cons	M
Ethnicity	E	Behavioral Processes	N
Education	F	Experiential Processes	O
Addiction	G	Income	P
Perceived Stress	H	Multiple Tests	*
Confidence - Positive Social	I		

Figure 30: Study 2: Conf Pos < 19

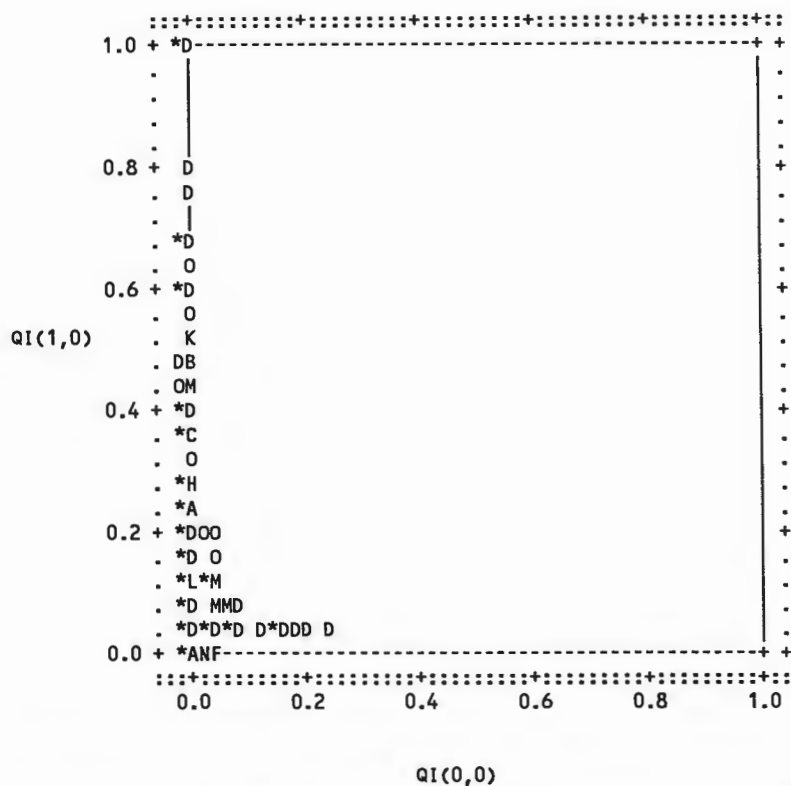
Study 2: QROC Graph Demonstrating Perceived Stress < 20 and Confidence (Negative Affect) < 19 and Confidence (Positive Social) < 19



Variable	Symbol	Variable	Symbol
Intervention	A	Confidence - Negative Affect	J
Stage	B	Confidence - Craving	K
Sex	C	Pros	L
Age	D	Cons	M
Ethnicity	E	Behavioral Processes	N
Education	F	Experiential Processes	O
Addiction	G	Income	P
Perceived Stress	H	Multiple Tests	*
Confidence - Positive Social	I		

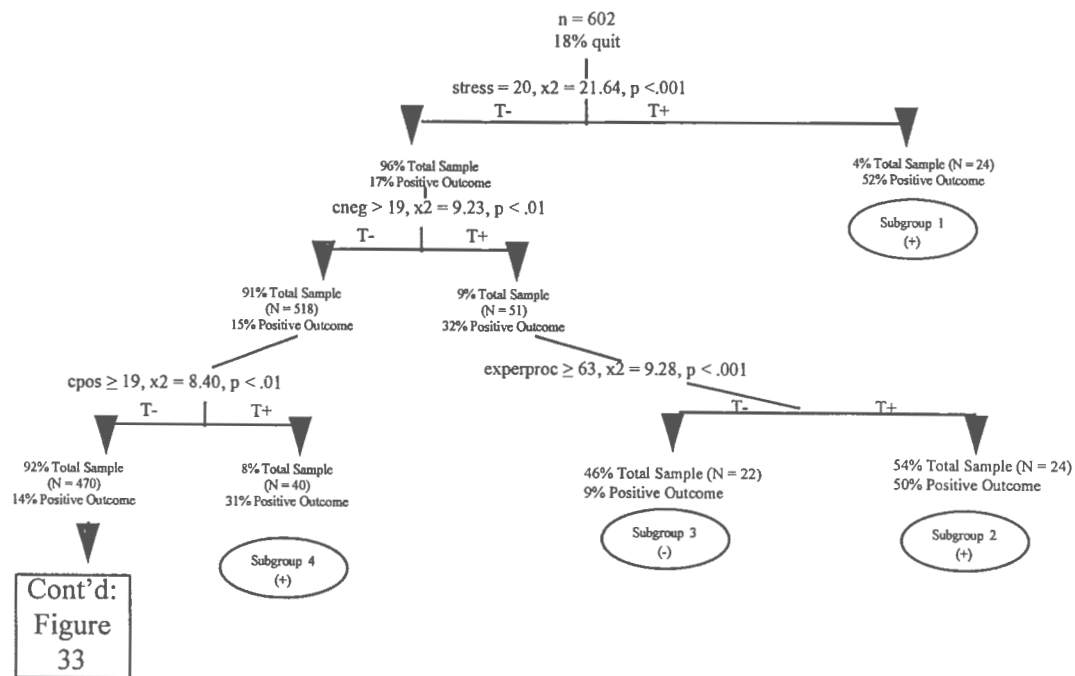
Figure 31: Study 2: Pros > 16

Study 2: QROC Graph Demonstrating Perceived Stress < 20 and Confidence (Negative Affect) < 19 and Confidence (Positive Social) < 19 and Pros > 16



Variable	Symbol	Variable	Symbol
Intervention	A	Confidence - Negative Affect	J
Stage	B	Confidence - Craving	K
Sex	C	Pros	L
Age	D	Cons	M
Ethnicity	E	Behavioral Processes	N
Education	F	Experiential Processes	O
Addiction	G	Income	P
Perceived Stress	H	Multiple Tests	*
Confidence - Positive Social	I		

Figure 32: Study 2: Final Algorithm (1)



Cont'd:
Figure
33

Figure 33: Study 2: Final Algorithm (2)

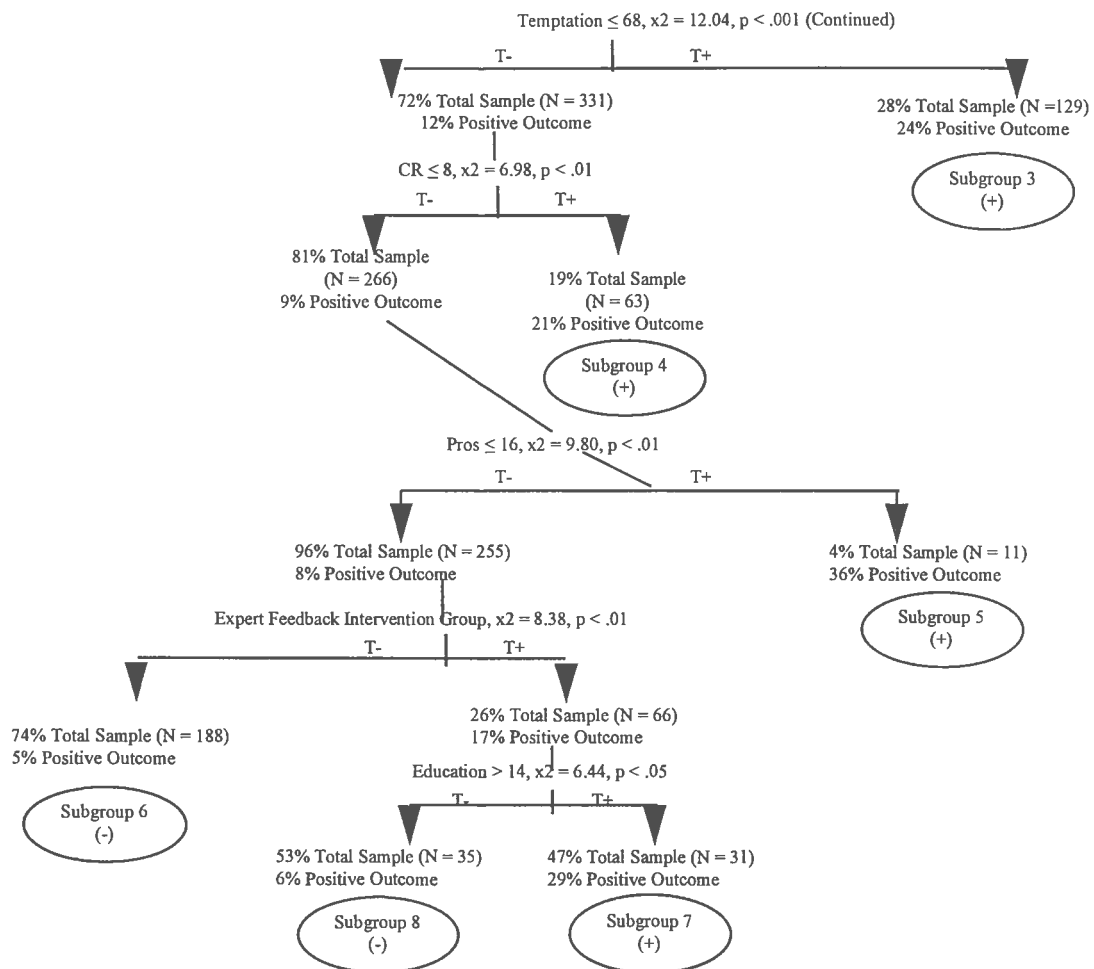


Figure 34: Study 3: Initial Algorithm (1)

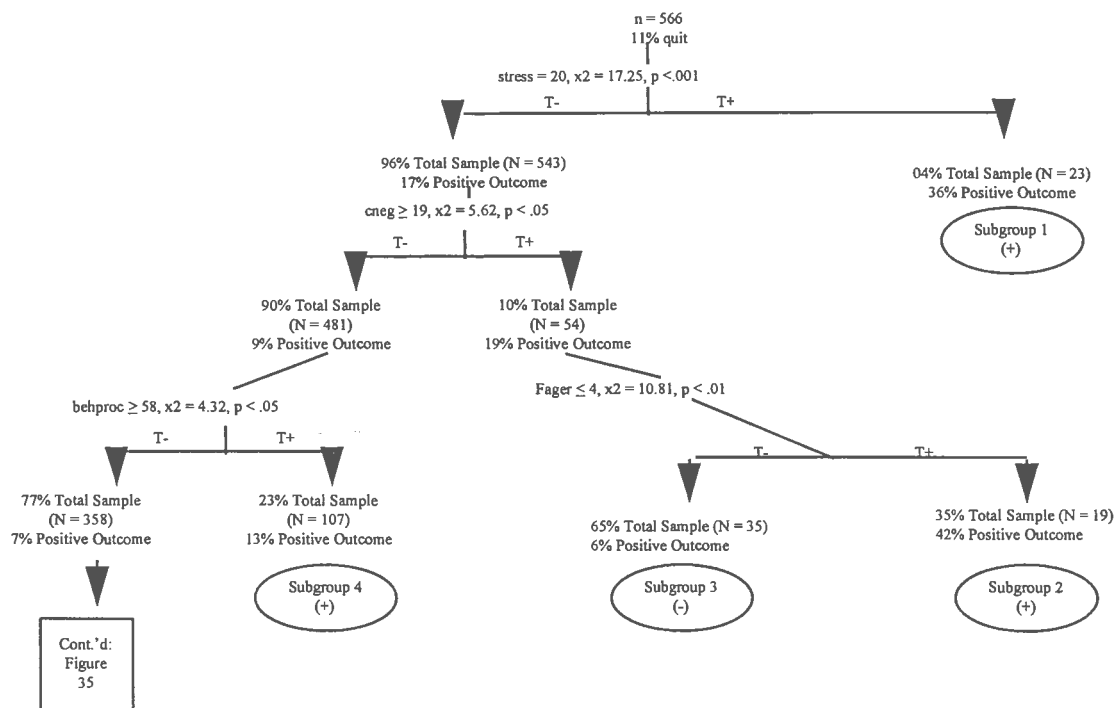


Figure 35: Study 3: Initial Algorithm (2)

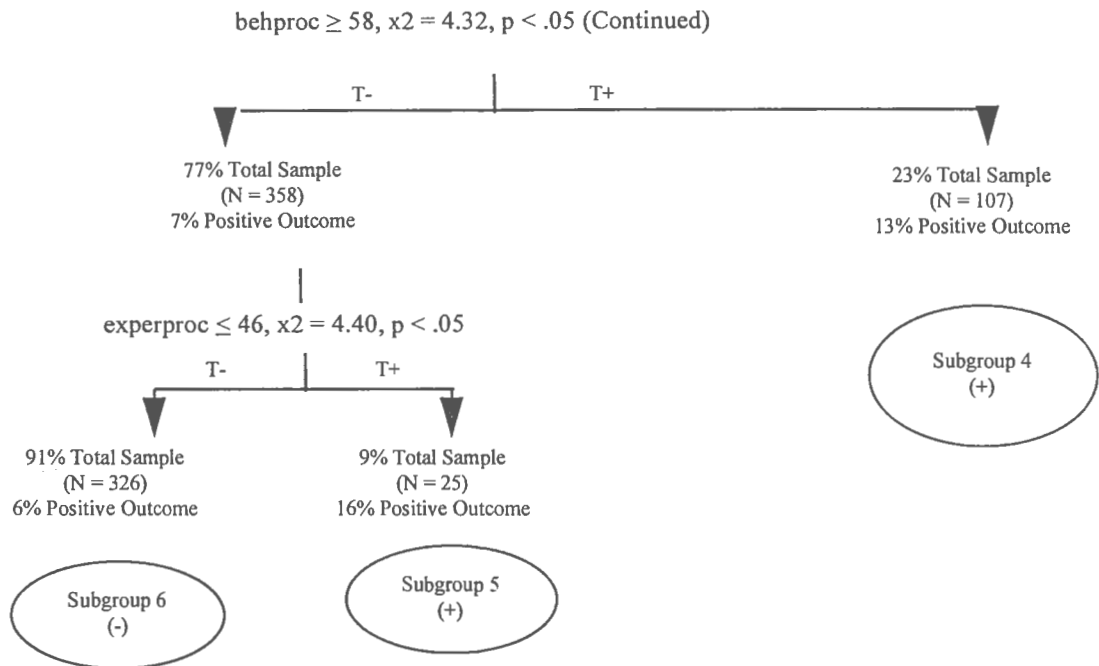


Figure 36: Study 3: Final Algorithm (1)

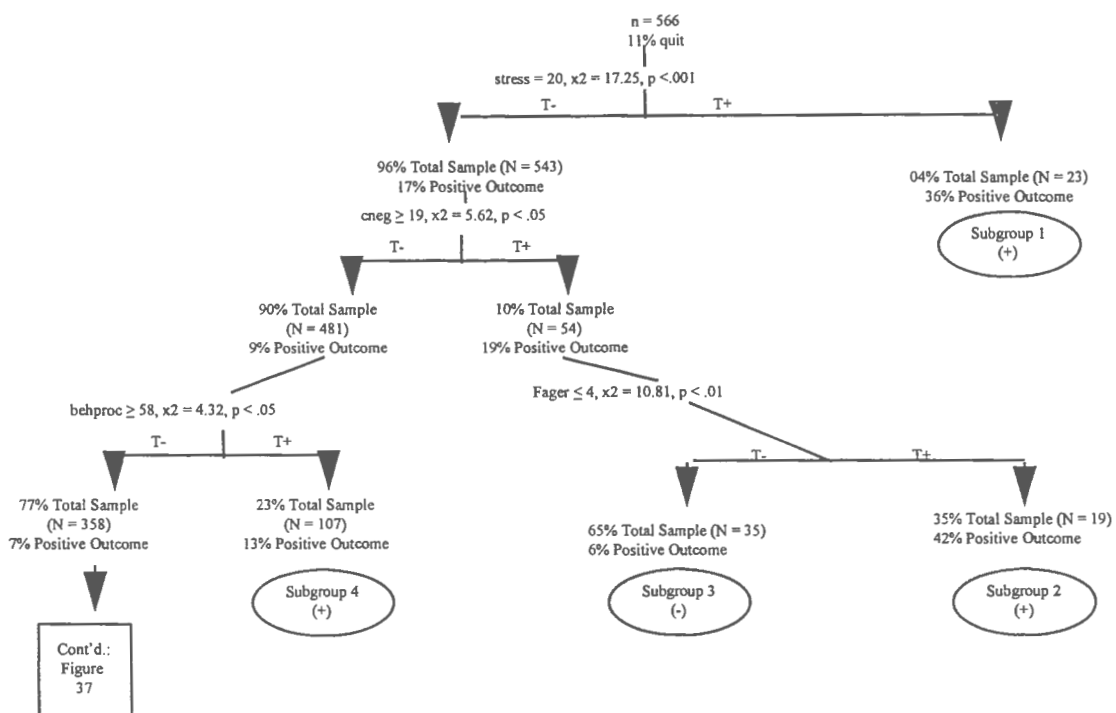
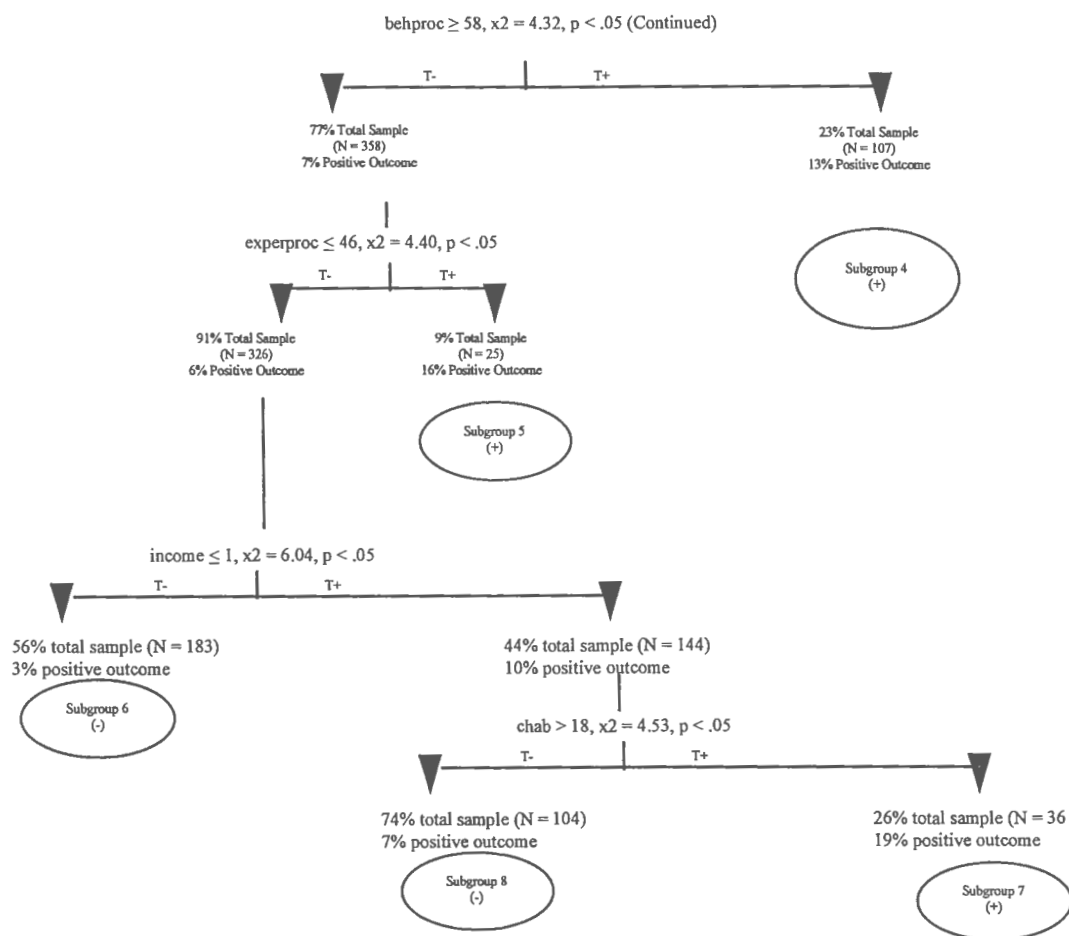


Figure 37: Study 3: Final Algorithm (2)



APPENDIX A

The Transtheoretical Model

Stages of Change

The Transtheoretical model posits that as individuals change a problem behavior, they move through a series of five stages. The stages of change provide a meaningful way to subdivide smokers and nonsmokers into groups that are significant for intervention or self-change (Prochaska & DiClemente, 1985). Movement through the stages is linear, but often occurs in a spiral pattern, so that as individuals move through the stages, they may at any point recycle back to an earlier stage. (e.g. Prochaska, DiClemente, & Norcross, 1992).

The first of the five stages is Precontemplation. Individuals in the Precontemplation stage are not intending to change their problem behavior. They may not perceive their behavior as a problem to their health, or they may be in denial of the negative health consequences. For example, a smoker in the Precontemplation stage may believe that other people get cancer from smoking, but he or she will not. Individuals in this stage may be resistant to pressures to force them to change.

The second stage of change is the Contemplation stage. Individuals in this stage are intending to change their behavior in the next six months. They are more open to information about their problem behavior than people in the Precontemplation stage. However, they are not yet ready to make a commitment to change in the near future. Contemplators are likely to spend time weighing the pros and cons of changing their behavior. It is possible for individuals to get stuck in this stage, so that although they

have been considering making a change for a long time, they are still not able to make a commitment to take action.

The next stage of change is the Preparation stage. In this stage, individuals have both intention to change soon (in the next thirty days), and have started taking behavioral steps toward change. For example, a smoker in this stage may have begun to cut down on number of cigarettes smoked per day and has made a 24-hour quit attempt.

The fourth stage of change is Action. Individuals in this stage have recently (one day to six months ago) changed their behavior and are actively practicing their new behavior. Whereas in the Preparation stage, smokers may meet the behavioral criteria for this stage by cutting down on the number of cigarettes smoked, to meet Action criteria individuals must completely give up smoking.

The fifth and final stage of change is Maintenance. In this stage individuals have refrained from the problem behavior for over six months. Their self-efficacy to not practice the problem behavior in most or all situations tends to be high.

Transtheoretical Model Predictors of Smoking Cessation

A number of variables have been found to be correlated with smoking cessation. Among these are variables included in the Transtheoretical model, such as self-efficacy (DiClemente, Prochaska, & Gibertini, 1985; Velicer, DiClemente, Rossi, & Prochaska, 1990), decisional balance (Velicer, DiClemente, Prochaska, & Brandenburg, 1985), and the processes of change (Prochaska & DiClemente, 1983; Prochaska, Velicer, DiClemente, & Fava, 1988).

Decisional Balance. The decisional balance construct used in the Transtheoretical model is based on Janis and Mann's (1977) conflict model, which assumes that sound decision making involves weighing potential gains and losses. Velicer, DiClemente, Prochaska, and Brandenburg (1985) found that decisional balance for smoking involved two orthogonal factors, which they labeled the pros and cons of decision making. The two factor structure of decisional balance has been confirmed in numerous health behaviors, including weight control, condom use, sunscreen use, cocaine-use cessation, and exercise acquisition (Prochaska et al., 1994). Predictable patterns have been found when decisional balance is related to the stages. For twelve different health behaviors, it was shown that the cons of changing outweighed the pros of changing in the Precontemplation stage. In eleven of these behaviors, the opposite was true in the Action stage (Prochaska et al., 1994). For smoking in particular, a predictable pattern has emerged where pros of smoking are higher than the cons in the Precontemplation stage (i.e. the pros of not changing are higher), cons of smoking rise in the Contemplation stage and cross over with pros, then both decrease in importance, with cons remaining slightly higher than pros, all the way through the maintenance stage (Prochaska & Goldstein, 1991; Velicer, DiClemente, Prochaska, and Brandenburg, 1985).

Self-efficacy and Temptation. Self-efficacy (Bandura, 1977; 1982), or the belief that one can perform a certain behavior, has been strongly related to actual ability to perform that behavior. Self-efficacy beliefs have been shown to affect the type of behaviors in which a person engages, length of persistence in the face of difficulties, and amount of effort expended (Bandura, 1977). In some circumstances, self-efficacy has

been found to be a better predictor of behavior than past behavior (Bandura, 1986; DiClemente, 1981).

Self-efficacy to not smoke has been found to be predictive of subjects' ability to maintain smoking cessation over time, and of movement through the stages of change. Higher self-efficacy scores in the first three stages are indicative of higher success in smoking cessation (DiClemente, Prochaska, & Gibertini, 1985). Self-efficacy to not smoke has also been shown to be related to habit strength, number of prior quit attempts, and the pros of smoking (DiClemente, Prochaska, & Gibertini, 1985), thus further establishing the construct's external validity.

Velicer, DiClemente, Rossi, and Prochaska (1990) used a hierarchical model to show that self-efficacy to not smoke consisted of three separate factors. Each of these factors represented situations or states in which a person might be tempted to smoke. The first factor consisted of positive or social situations. The second factor consisted of items that described negative affect or situations. The final factor reflected the cravings for cigarettes or addiction to smoking. This hierarchical model was conceptualized by the authors as reflecting change that occurs over time. The three self-efficacy factors may not be differentiated in early stages such as Precontemplation and Contemplation. People in these stages would have equally low self-efficacy to not smoke in any situation. However, in the Preparation and Action stages, individual differences result in unequal efficacy levels among the three factors. Specific situations may be more tempting for some individuals than others. In the Maintenance stage, the three factors may again be

undifferentiated, because people who have reached this stage have high efficacy to not smoke in all situations.

Temptation to smoke has also been found to be related to smoking cessation (DiClemente, Prochaska, & Gibertini, 1985). This construct has been found to have a fairly strong correlation with self-efficacy (-.57). The two constructs were both able to distinguish groups of people in different stages of change. Whereas self-efficacy to not smoke tends to increase as individuals progress through the stages of change, temptation to smoke tends to decrease.

Processes of Change. Processes of change are independent variables in the Transtheoretical model that assess which experiential and behavioral tools people use to change their problem behaviors. Based on research findings indicating that most therapies were approximately equivalent in effectiveness, Prochaska & DiClemente (1983) theorized that there must be underlying processes common to most forms of therapy and to behavior change in general. Processes of change can be viewed as a combination of activities and experiences that a person employs as coping mechanisms while working to change a behavior (DiClemente & Prochaska, 1985). Each process can encompass multiple techniques and methods that may traditionally have been associated with quite disparate forms of therapy (Prochaska, DiClemente, & Norcross, 1992).

It has been found that ten or eleven similar processes of change are employed across a wide range of behaviors, including smoking, weight control, and psychological distress (Prochaska & DiClemente, 1985). These processes have also been found to load on two higher order factors, which have been labeled experiential and behavioral

processes (Prochaska, Velicer, DiClemente, & Fava, 1988). The experiential factor consists of five processes all of which generally involve internal experiences. These include Consciousness Raising, Self-reevaluation, Environmental Reevaluation, Social Liberation, and Dramatic Relief. Consciousness Raising involves seeking out and learning information about the problem behavior. Self-reevaluation is assessing how one thinks and feels about oneself with respect to the problem behavior. Environmental reevaluation entails assessing how one's behavior affects others in the individual's environment. Social Liberation is becoming aware of alternatives for the problem behavior that can be found in the individual's environment. Dramatic Relief entails experiencing emotional reactions to information about the negative consequences of one's problem behavior.

The behavioral processes generally involve overt and observable activities. These five processes are labeled Stimulus Control, Counterconditioning, Reinforcement Management, Helping relationships, and Self Liberation. Stimulus control entails either removing tempting objects from the person's immediate environment or placing things in the environment that may encourage a positive behavior. Counterconditioning involves substituting alternatives for the problem behavior. An example could be chewing gum instead of smoking. Reinforcement Management is being rewarded by oneself or by others for changing. Helping relationships encompass opening oneself up to and receiving support from someone close about the behavior change. Self-liberation is making the commitment to oneself to change the problem behavior.

The use of experiential and behavioral processes peak at different times across the stages of change (DiClemente & Prochaska, 1985; Prochaska, DiClemente, & Norcross, 1992) . Individuals in the Precontemplation stage tend to use all ten processes less than individuals in any other stage. The experiential processes are used most in the pre-Action stages. The behavioral processes are used most in Action and the stages around Action. Although there is some continued use of behavioral processes in the Maintenance stage for smoking cessation, use of processes overall appears to decrease in this stage. This is most likely because people in Maintenance no longer have to work as hard at the new behavior as people in Action to maintain their change.

In longitudinal studies, processes of change have been shown to predict stage movement over time (Prochaska, DiClemente, Velicer, Ginpil, & Norcross, 1985; Wilcox, Prochaska, Velicer, & DiClemente, 1985). In a two-year longitudinal study of smokers, Prochaska, DiClemente, Velicer, Rossi, & Guadagnoli (1991) found several patterns of behavior change. For example, those in the Stable pattern remained in the Precontemplation stage at all five data collection points. Use of processes remained stable over time and in eight of the ten processes, this group was between 0.4 and 1.4 standard deviations below the mean. On the other hand, in the Progressing group, in which people progressed from Contemplation to Maintenance over the two years, use of individual processes peaked and waned at different points. Many of the experiential processes peaked during the Contemplation stage, while many of the behavioral processes increased in use between the Contemplation and Action stages. The use of these processes then leveled off or waned in the Maintenance stage. Thus, use of certain

processes in particular stages of change is predictive of forward movement through the stages.

MEASURES

Staging for Smoking Cessation

Are you currently a smoker?

yes no

Are you seriously considering quitting in the next six months?

yes no already quit

Are you planning to quit in the next thirty days?

yes no already quit

Have you reduced the number of cigarettes you smoke in the last month?

yes no I don't smoke

Since you started smoking regularly, have you ever quit for a period of at least six months?

yes no

Point Prevalence Outcome

Are you currently a smoker?

yes no

Have you smoked a cigarette, even a puff, in the last seven days?

yes no

Perceived Stress Scale

In the last month, how often have you felt confident about your ability to handle your personal problems?

Never Almost Never Sometimes Fairly Often Very Often

In the last month how often have you felt that you were unable to control the important things in your life?

Never Almost Never Sometimes Fairly Often Very Often

In the last month how often have you felt that things were going your way?

Never Almost Never Sometimes Fairly Often Very Often

In the last month how often have you felt difficulties were piling up so high that you could not overcome them?

Never Almost Never Sometimes Fairly Often Very Often

Processes of Change

The following experiences can effect the smoking pattern of some people. Think of any similar experiences you may be currently having or have had in the last month. Then rate the frequency of each event on a 5 point scale with 5 = Repeatedly and 1 = Never.

Never Seldom Occasionally Often Repeatedly

1. Special people in my life accept me the same whether I smoke or not
2. I see "No Smoking" signs in public buildings
3. I can be open with at least one special person about my experience with smoking
4. I tell myself I can choose to smoke or not
5. Instead of smoking I engage in some physical activity
6. I recall articles dealing with the problems of quitting smoking
7. I notice that public places have sections set aside for smokers
8. I recall information people have personally given me on the benefits of quitting smoking
9. I am considering the belief that people quitting smoking will help to improve the world
10. I think about information from articles and advertisements on how to stop smoking
11. Remembering studies about illnesses caused by smoking upsets me
12. Other people in my daily life try to make me feel good when I don't smoke
13. I tell myself I am able to quit smoking if I want to

14. I have someone who listens when I need to talk about my smoking
15. I remove things from my home that remind me of smoking
16. I tell myself that if I try hard enough I can keep from smoking
17. I recall information people have personally given me on how to stop smoking
18. I make commitments not to smoke
19. I reward myself when I don't smoke
20. I notice that nonsmokers are asserting their rights
21. I stop to think that smoking is polluting the environment
22. I can expect to be rewarded by others if I don't smoke
23. I keep things around my work place that remind me not to smoke
24. I find society changing in ways that make it easier for the nonsmoker
25. I get upset when I think about my smoking
26. I find that doing other things with my hands is a good substitute for smoking
27. When I am tempted to smoke, I think about something else
28. I do something else instead of smoking when I need to relax or deal with tension
29. I remove things from my place of work that remind me of smoking
30. Warnings about the health hazards of smoking move me emotionally
31. Dramatic portrayals of the evils of smoking affect me emotionally
32. I react emotionally to warnings about smoking cigarettes
33. I am rewarded by others if I don't smoke
34. I consider the view that smoking can be harmful to the environment
35. I reassess the fact that being content with myself includes changing the smoking habit

36. I consciously struggle with the issue that smoking contradicts my view of myself as a caring and responsible person
37. I put things around my home that remind me not to smoke
38. My dependency on cigarettes makes me feel disappointed in myself
39. I am considering the idea that the world around me would be a better place without my smoking
40. I have someone whom I can count on when I am having problems with smoking

Decisional Balance

The following statements represent different opinions about smoking. Please rate HOW IMPORTANT each statement is to you according to the following 5 point scale with 5 = Extremely important and 1 = Not important.

Not Important	Slightly Important	Moderately Important
Very Important	Extremely Important	

1. Smoking cigarettes is pleasurable
2. My smoking affects the health of others
3. I like the image of a cigarette smoker
4. Others close to me would suffer if I became ill from smoking
5. I am relaxed and therefore more pleasant when smoking
6. Because I continue to smoke, some people I know think that I lack the character to quit
7. If I try to stop smoking I'll be irritable and a pain to be around
8. Smoking cigarettes is hazardous to my health
9. My family and friends like me better when I am happily smoking than when I am miserably trying to quit
10. I'm embarrassed to have to smoke
11. I like myself better when I smoke
12. My cigarette smoking bothers other people

13. Smoking helps me concentrate and do better work
14. people think I'm foolish for ignoring the warning about cigarette smoking
15. Smoking cigarettes relieves tension
16. People close to me disapprove of my smoking
17. By continuing to smoke I feel I am making my own decisions
18. I'm foolish to ignore the warnings about cigarettes
19. After not smoking for a while a cigarette makes me feel great
20. I would be more energetic right now if I didn't smoke

Smoking Abstinence Self-Efficacy (SASE)

Listed below are situations which lead some people to smoke. We would like to know how confident you are that you would not smoke in these situations. Please answer the following questions by using a 5 point scale with 5 = Extremely confident and 1 = Not at all confident.

Not at all Confident	Not Very Confident	Moderately Confident
	Very Confident	Extremely Confident

1. At a bar or a cocktail lounge having a drink
2. When I am desiring a cigarette
3. When things are just not going the way I want and I am frustrated
4. With my spouse or close friend who is smoking
5. When there are arguments and conflicts with my family
6. When I am happy and celebrating
7. When I am very angry about something or someone
8. When I would experience an emotional crisis, such as an accident or death in the family
9. When I see someone smoking and enjoying it
10. Over coffee while talking and relaxing
11. When I realize that quitting smoking is an extremely difficult task for me
12. When I am craving a cigarette

13. When I first get up in the morning
14. When I feel I need a lift
15. When I begin to let down on my concern about my health and am less physically active
16. With friends at a party
17. When I wake up in the morning and face a tough day
18. When I am extremely depressed
19. When I am extremely anxious and stressed
20. When I realize I haven't smoked for a while

Smoking Temptation Scale

Listed below are situations that lead some people to smoke. We would like to know how tempted you may be to smoke in each situation. Please answer the following questions by using a 5 point scale with 5 = Extremely Tempted and 1 = Not at all Tempted.

Not at all Tempted Not Very Tempted Moderately Tempted
Very Tempted Extremely Tempted

1. At a bar or a cocktail lounge having a drink
2. When I am desiring a cigarette
3. When things are just not going the way I want and I am frustrated
4. With my spouse or close friend who is smoking
5. When there are arguments and conflicts with my family
6. When I am happy and celebrating
7. When I am very angry about something or someone
8. When I would experience an emotional crisis, such as an accident or death in the family
9. When I see someone smoking and enjoying it
10. Over coffee while talking and relaxing
11. When I realize that quitting smoking is an extremely difficult task for me
12. When I am craving a cigarette
13. When I first get up in the morning

14. When I feel I need a lift
15. When I begin to let down on my concern about my health and am less physically active
16. With friends at a party
17. When I wake up in the morning and face a tough day
18. When I am extremely depressed
19. When I am extremely anxious and stressed
20. When I realize I haven't smoked for a while

Fagerstrom Tolerance Questionnaire

How many cigarettes a day do you smoke?

Do you smoke more in the morning than during the rest of the day?

yes no I don't smoke

How soon after you wake up do you smoke your first cigarette?

Which cigarette would you hate most to give up?

not first first of day

Do you find it difficult to refrain from smoking in places where it is forbidden, for example, church, cinema, etc.?

yes no I don't smoke

Do you continue to smoke if you are so ill that you are in bed most of the day?

yes no I don't smoke

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